Agriculture, Aggregation, Wage Gaps, and Cross-Country Income Differences

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Abstract

In spite of its low productivity, agriculture employs most of the labor force in countries in the lower part of the world income distribution. Moreover, agriculture differs from other activities in its intensive use of land. We show that ignoring agriculture, as most one-sector aggregate models do, gives rise to substantially biased results regarding the sources of cross-country income differences. We first show that standard Solow residuals underestimate underlying productivity differences across countries. Specifically, Solow residuals are less disperse than both agricultural and nonagricultural TFPs. More importantly, we show that the large labor productivity gap between agriculture and nonagriculture is not accounted for by migration costs or schooling differences. Instead, the gap seems to be explained by the particularly low *quality* of human capital in rural areas. This finding implies that most of the income dispersion across countries is not due to TFP differences but to differences in factor endowments, particularly human capital in rural areas.

1 Introduction

The study of the sources of cross-country income differences is typically conducted using one-sector models with a common Cobb-Douglas technology for all countries (e.g., Klenow and Rodríguez-Clare, 1997; Prescott, 1998; and Hall and Jones, 1999). This methodology abstracts from differences in sectoral composition across countries as well as differences in production technologies across sectors.

However, four well-known observations in the economic development literature make apparent important sectoral composition differences across countries. First, agriculture accounts for a large

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fraction of the production in less developed countries, and its importance decreases with the level of development. Second, the share of labor force in agriculture tends to be even larger than the share of agriculture in total output, and this share also decreases with the level of development. Third, the productivity of labor in agriculture is significantly lower than in nonagriculture, particularly for less developed countries, as illustrated in Figure 1. Fourth, agriculture is more intensive in the use of land than nonagriculture. Do these sectoral differences have aggregate consequences?

To answer this question, this paper studies the sources of cross-country income differences in a world composed by a large number of small open economies, each of which produces an agricultural and a nonagricultural good. We characterize the aggregate production function of a representative economy for the general case in which agricultural and nonagricultural activities differ in their land, capital, and quality-adjusted labor intensities. We then analyze potential pitfalls that occur when this aggregate production function is approximated by a Cobb-Douglas function. In particular, we assess the extent to which the Solow residuals obtained from this approximation properly characterize the underlying technological differences across countries in the model.

For the quantitative analysis, we consider versions of the model that can account for the four observations mentioned above. Of particular importance is the explanation for the observed labor productivity gap across sectors, or wage gap for short. As illustrated in Figure 1, nonagricultural workers produce 10 to 25 times more than agricultural workers in many of the very poor countries. A natural explanation for the wage gap is that urban and rural workers differ substantially in their human capitals. Previous studies, with the exception of Caselli (2004), have generally not considered this possibility, mostly due to the lack of information on rural and urban human capital across countries. We address this problem here. We use available data from UNESCO to construct series of human capital for urban and rural areas for a cross section of countries. Although the data is limited, we find a strong relationship between rural and urban years of schooling and the total average years of schooling. We exploit this relationship to extrapolate to all countries in our sample. Sectoral measures of schooling are then transformed into measures of human capital using a standard Mincer equation.

The analysis yields three main results. The first result is that standard Solow residuals underestimate productivity differences across countries. Specifically, we find that the dispersion of *both* agricultural and nonagricultural TFPs in the two-sector model is larger than the dispersion of Solow residuals. The result is surprising since it implies that the dispersion of aggregate TFPs computed in a one-sector models is not, as one would expect, a weighted average of sectoral TFP dispersions. Instead, Solow residuals provide a sort of lower bound for the underlying sectoral productivity differences. This is because Solow residuals capture not only technological differences, but also a "diversification effect." Economies with low physical capital endowments can diversify into the production of land-intensive goods. These gains from diversification are captured in standard accounting exercises as larger Solow residuals for those countries.

The practical content of our first finding is that productivity differences across countries are larger than previously thought, a result that deepens the puzzle of why countries differ so much in their efficiency levels. The magnitude of the adjustment depends on parameter values, in particular on the intensity of land in agriculture and nonagriculture, as well as the precise explanation of the wage gap. A conservative exercise shows that TFPs of very poor countries, typically the ones with large agricultural sectors, are below the technological frontier between 10 to 40% more than what Solow residuals would suggest. For example, according to Solow residuals the technological lag of Somalia relative to the frontier is of around 69%. We find instead that Somalia's technological lag is of around 78% in nonagriculture and 88% in agriculture. Our results show that poor countries are not properly portrayed in standard accounting exercises, which have traditionally been designed to fit the characteristics of rich countries.

Our second main result is that differences in schooling across sectors can only account for a small fraction of the observed wage gap. We find that once controlling for schooling, the ratio of labor productivity in nonagriculture relative to agriculture is on the order of 10 to 18 in the poorest countries. Although we document that there is a gap in years of schooling between rural and urban areas, and that this gap is larger in poor than in rich countries, the differences are just not sizeable enough to explain a major part of the wage gap.

This result compelled us to study alternative explanations of the wage gap. For this purpose, we study the wage gap resulting from a dynamic version of the Harris and Todaro (1970) migration model that allows for differences in schooling as well as quality of human capital. In particular, we consider the possibility that human capital in poor countries (where most workers are in rural areas) is lower than what is implied by Mincerian equations, due to poor *quality*. This poor quality can be interpreted as the outcome of low parental human capital or low quality of schooling. In addition, we think of this quality as embodied in the worker. We compute quality differences across rural-urban areas as the residuals required to fully account for any wage gap remaining after controlling for schooling differences and migration costs. Migration costs are calibrated using U.S. data and a variety of simulations. The quality of human capital in urban areas is assumed to be equal across countries, a normalization that prevents poor countries from having better urban human capital than rich countries. Finally, we compute aggregate stocks of human capital for each country by adding up sectoral stocks of human capital. Our quality-adjusted series of human capital turn out to be significantly different from the ones computed using standard Mincer equations, particularly for poor countries. This is because most of the wage gap in poor countries is not accounted for by schooling or migration costs.

Finally, we revisit level accounting results using our quality-adjusted series of human capital. Our third main result is that the contribution of TFP is reduced significantly, at least 25 percentage points, when our series of human capital are used. The intuition for this finding is the following: the wage gap seems to be caused by particularly low levels of human capital in rural areas. As a result, human capital measures that are only based on rural education attainments need to be adjusted downward to account for the gap. This adjustment mainly affects poor countries, which are typically the ones with large wage gaps and large rural population. Thus, the adjustment widens cross-country differences in human capital, and increases the role of human capital in explaining cross-country income differences. This explanation of the wage gap is consistent with the results of Manuelli and Seshadri (2004), who find that human capital series in poor countries are overestimated. Here, we provide a quantitative support for this claim based on sectoral information on labor productivity.

Our paper is closely related to recent quantitative work on agriculture and development by Caselli (2004), Dalgaard and Chanda (2003), Gollin, Parente and Rogerson (2004), Restuccia, Yang and Zhu (2003), and Vollrath (2005), among others. There are two important differences between previous papers and ours. First, our work focuses on efficient allocations of factors within a country, a standard assumption in the growth accounting literature, and a useful benchmark to consider. In particular, we do not take the wage gap as direct evidence of inefficient allocations, but instead ask whether potential explanations for the gap within an efficient framework are able to plausibly explain its magnitude. Our paper is then complementary to those directly assuming inefficiencies. The efficiency approach used here is more closely related to Caselli (2004, Section 6). He explores some aggregate consequences of a two-sector model that explicitly considers land, and provides a partial explanation for the wage gap within this framework. He finds that sectoral composition does not matter for aggregate results and, in fact, it reinforces the message of one-sector models. A limitation of Caselli's work is that most of the wage gap is left unexplained. We show that by requiring the model to explain the wage gap, standard level accounting results are overturned.

A second distinguishing feature of our work is the focus on finding links between accounting exercises in one and two-sector models. We develop results that allow the application of techniques from one-sector models into two-sector models. In particular, the additive nature of multisectoral models makes it difficult to decompose the variance of world income between factors and TFP. We propose a simple methodology that delivers a full variance decomposition. This methodology allows us to provide a clear intuition of the extent to which Solow residuals properly capture productivity differentials.

The remainder of the paper is organized as follows. Section 2 presents our benchmark model and develops some analytical results. In addition, it shows that the cross-country dispersion of sectoral TFPs is larger than the dispersion of standard Solow residuals, and it examines level accounting exercises using data for a cross-section of countries in 1988. In Section 3 we study the implications of our baseline methodology for the wage gap and find important limitations. We extent the baseline model to better match the wage gap, adjust the human capital series, and revisit the question about the sources of cross country income differences. Concluding comments are presented in Section 4.

2 The Benchmark Model

In this section we derive the aggregate production function for a two-sector, three-factor economy. Our results can be easily extended to the more general case in which the number of sectors is smaller than the number of factors.[1] We show analytically that Solow residuals are less disperse than nonagricultural TFPs, and illustrate this prediction using data for a cross-section of countries.

[1] As it is well known in the trade literature, when the number of sectors is larger than the number of factors, some of the sectors will not operate. In addition, since in our model economy the number of sectors is less than the number of factors, factor prices are not equalized across countries because they depend on the total factor endowments of each country. In the language of the trade literature, factor price equalization does not hold.

We also show that for plausible calibrations agricultural TFPs are more disperse across countries than nonagricultural TFPs. These results together mean that the dispersion of Solow residuals is not, as one would expect, a weighted average of sectoral TFP dispersions.[2]

Consider a world composed of a large number of small open economies. There are two goods, agriculture a and nonagriculture n, and three factors of production, physical capital K, quality adjusted or effective labor H, and arable land T. Denote also by K, H, and T the aggregate quantities of those factors in a given country. Factors are mobile across sectors within a country, but internationally immobile. Goods can be traded internationally, and output prices, p_a and p_n, are determined in international markets.[3] Each country takes output prices as given. The assumption of a small open economy allows us to focus on the production side of the economy.

A country can produce good i, for $i = \{a, n\}$, using a constant returns to scale production function, $\overline{A}_i F^i(K_i, T_i, H_i)$. Here $\overline{A}_i$ is the country-specific TFP of good i. The function F^i is identical across countries. Assume that $F^i(K_i, T_i, H_i) = K_i^{\alpha_i^K} T_i^{\alpha_i^T} H_i^{\alpha_i^H}$ with $\alpha_i^K + \alpha_i^T + \alpha_i^H = 1$ and $0 < \alpha_i^f < 1$ for $f = \{K, T, H\}$. Notice that all factors are essential for the production of good i. We assume agriculture to be more land intensive than nonagriculture in the sense that $\alpha_a^T \geq \alpha_n^T$.

2.1 The Efficient Level of Production

Consider the efficient level of total production in a particular country. The assumption that factors are allocated efficiently has also been made by the *development accounting* literature (e.g. Klenow and Rodríguez-Clare, 1997; Prescott, 1998; and Hall and Jones, 1999), and therefore it is the natural assumption for our purposes. However, efficiency is not a standard assumption in the *development* literature, which often stresses the dual or segmented nature of labor markets (e.g. Dalgaard and Chanda, 2003; and Vollrath, 2005). Evidence on segmented markets is mixed, but some empirical findings suggests that labor markets work better than what is typically recognized in the development literature (e.g., Kannappan, 1985; Hatton and Williamson, 1991; Magnac, 1991; Tannen, 1991; and Pratap and Quintin, 2003.) We do not introduce distortions in the model mainly due to the difficulty of finding cross-country information on specific barriers leading to segmentation, such as taxes or restrictions to migration. The approach we take in this paper

[2]We thank Francesco Caselli for pointing this out.

[3]Here we abstract from nontraded goods. In principle, some types of both agricultural and nonagricultural goods may be nontraded. We do not consider this in our analysis mainly due to the lack of cross-country data.

is to ask whether observed differences in the marginal product of factors across sectors can be quantitatively accounted for without appealing to any inefficiencies.

Denote by $A_i \equiv p_i \overline{A}_i$ the price-adjusted TFP level in sector i. The central planner in each country chooses the allocation of factors across sectors that maximizes the aggregate level of output Y,

$$Y = G(K, T, H; \overrightarrow{A}) \equiv \max_{\{K_i, H_i, T_i\}_{i=a,n}} \left[A_a F^a(K_a, T_a, H_a) + A_n F^n(K_n, T_n, H_n) \right], \tag{1}$$

subject to,

$$K_a + K_n = K; \qquad H_a + H_n = H; \qquad T_a + T_n = T; \tag{2}$$

for a given vector $\overrightarrow{A} \equiv [A_a, A_n]$. An efficient allocation of factors may imply full specialization. For our purpose, however, all countries in our sample produce both goods. Consequently, we assume that parameter values in each country, in particular $\overline{A}_a$ and $\overline{A}_n$, are such that an efficient allocation is interior.

The objective of this section is to characterize function G. To gain some intuition, consider a case in which functions F^i are identical across sectors ($F^i = F$). In this case, the requirement of an interior solution imposes the additional restriction $A_a = A_n$. As a result, the aggregate production function G takes the form $G(K, T, H; \overrightarrow{A}) = AF(K, T, H)$. This is the case typically analyzed in the literature, and it requires sectoral TFPs (adjusted by prices) to be identical across sectors. These results, however, do not hold when $F^a \neq F^n$. We now derive the aggregate production function for this more general case.

Denote $k \equiv K/H$ and $t \equiv T/H$ the ratios of capital and land to effective units of labor, and define $B \equiv A_n/A_a$ as the ratio of price-adjusted sectoral TFPs. Let $k_i^* \equiv K_i^*/H_i^* = k_i(K, T, H; \overrightarrow{A})$ and $t_i^* \equiv T_i^*/H_i^* = t_i(K, T, H; \overrightarrow{A})$ be the optimal allocation rules of capital and land per unit of effective labor in sector $i = \{a, n\}$. A property of these allocation rules is that they depend only on the ratios (k, t; B) but not on the exact levels $(K, T, H; \overrightarrow{A})$, i.e., $k_i(K, T, H; \overrightarrow{A}) = k_i(k, t; B)$ and $t_i(K, T, H; \overrightarrow{A}) = t_i(k, t; B)$. We can now state the main finding of this section, a multiplicative formulation for the aggregate production function.

Proposition 1 For any $i = \{a, n\}$, efficient production satisfies

$$Y = G(K, T, H; \overrightarrow{A}) = \underbrace{A_i}_{\text{TFP}} \quad \underbrace{F^i(K, T, H)}_{\text{Factors}} \quad \underbrace{Z_i(k, t; B)}_{\text{Adjustment}} \tag{3}$$

where

$$Z_i(k,t;B) = \left(\frac{k_i^*}{k}\right)^{\alpha_i^K} \left(\frac{t_i^*}{t}\right)^{\alpha_i^T} \left[\alpha_i^K \frac{k}{k_i^*} + \alpha_i^T \frac{t}{t_i^*} + \alpha_i^H\right]. \tag{4}$$

Proof: see appendix A.

To better understand Proposition 1, notice first that Y does not measure sector i's output, but *total* output. Second, notice that the TFP term above corresponds to sector i's TFP, while the Cobb-Douglas term $F^i(K,T,H)$ uses the technology in sector i, but the total amount of factors of the economy. Third, the adjustment term Z_i relates the optimal ratios of capital and land to labor in sector i, i.e. k_i^* and t_i^*, to the aggregate ratios k and t. If the sectoral ratios are equal to the aggregate ones, then Z_i equals 1 and G adopts the standard Cobb-Douglas form. The latter case occurs when the production functions are identical across sectors. Finally, the representation of aggregate output in (3) requires the use of a *reference* sector i. For an interior solution, the exact choice is irrelevant to determine total output, but it is relevant to determine the size of each component in the equation.

The main virtue of equation (3) is that it provides a multiplicative formulation of aggregate production in three fundamental components. The first two components of the formulation are the traditional TFP and factors components. They describe the total production of the economy if all of factors are placed in only one sector (sector i). Such decision is suboptimal since, by assumption, the solution is interior. The term Z_i, which is necessarily larger than 1, adjusts the output implied by the first two terms to obtain the efficient level of output. Thus, Z_i captures gains from diversification. A property of the adjustment term Z_i is that it is homogenous of degree zero in TFP levels: it only depends on the *ratio* B of price-adjusted sectoral TFPs, but not on the TFP *levels* themselves. This property of Z_i is used in Section 4 to justify a decomposition of output based on (3).

Equation (3) shows that the aggregate production function is not Cobb-Douglas unless $F^a = F^n$. At first glance this may be regarded as a limitation because Cobb-Douglas functions imply a constant labor share, a property consistent with important empirical evidence. However, G also produces a constant labor share under the additional restriction $\alpha_a^H = \alpha_n^H$. We impose this restriction in most of the quantitative results below.

2.2 A Graphical Example without Land

To develop some intuition on the properties of G and Z_i, consider for a moment a case with only two factors of production, K and H, no land, and with agriculture being more labor intensive: $\alpha_a^T = \alpha_n^T = 0$ and $\alpha_n^K > \alpha_a^K$. For graphical purposes it is convenient to express all variables in log terms. Figure 2 illustrates $g_i \equiv \ln\left(A_i F^i(k,1)\right)$ for $i = \{a, n\}$ as functions of $k' \equiv \ln(k)$. g_i is (the log of) *total* output per effective worker if the economy only produces good i. The optimal (log) level of production, $g^* \equiv \ln(G(k, 1; \overrightarrow{A}))$, coincides with g_a for $k' < \underline{k'}$, and with g_n for $k' > \overline{k}'$. For $k \in (k', \overline{k}')$, the cone of diversification, g^* is above both g_a and g_n. By assumption, all the countries we study are diversified, so their k's lie on the interval $(\underline{k'}, \overline{k}')$.

Proposition 1 states that the aggregate production can be expressed in terms of either g_a or g_n and an adjustment term. The vertical distance between g^* and g_i is the adjustment term $z_i \equiv \ln(Z_i)$. Notice that along the cone of diversification, z_a increases with k' while z_n decreases with k'. This implies that the adjustment is larger for richer countries if the reference sector is agriculture, but smaller for richer countries if the reference sector is nonagriculture.

We can use Figure 2 to illustrate a pitfall that arises when the production function g^* is approximated by a Cobb-Douglas. More specifically, consider a typical accounting exercise that ignores the agricultural sector, and approximates the aggregate production function g^*, by the nonagricultural production function g_n. This approximation is relatively accurate for rich countries (those with large k'), which produce mostly nonagriculture goods. However, the approximation is less satisfactory for poorer countries, which have lower k' and larger agricultural sectors.

A consequence of approximating g^* by g_n is that the Solow residuals of this approximation do not reflect technological or efficiency differences across countries. To see this more clearly, consider two countries that are equally efficient in the use of factors in both sectors, i.e. countries with identical A_a and A_n, but different capital stocks. Assume that one country has capital $\underline{k'}$ and produces y_p (in logs), while the other has capital stock $\overline{k}'$ and produces y_r (see Figure 2). Given that g^* is approximated by g_n, the (log of) Solow residuals is $s = y - \alpha_n^K k'$. The residual for the rich country is given by $s_r = y_r - \alpha_n^K \overline{k}' = \ln A_n$, that is, the nonagricultural TFP. In contrast the residual for the poor country is $s_p = y_p - \alpha_n^K \underline{k'} = \ln A_n + z_p > \ln A_n$. Thus, the Solow residual for the poor country does not correspond to any TFP level, and it actually overestimates the efficiency level of nonagriculture in that country.

2.3 Land and Solow Residuals

The previous example suggests that Solow residuals do not capture underlying productivity differences across countries because factors shares are not constant as the Cobb-Douglas formulation implies. In the example, this occurs because economies go from being labor intensive to being capital intensive as they develop. In practice, the evidence suggests that in fact economies become less land-labor intensive and more capital-labor intensive as they develop. We now show that the intuition in Figure 2 holds for the more general case in which land is a factor of production, and the development process is one that substitutes land for capital instead of labor for capital.

Consider a typical accounting exercise along the lines of Hall and Jones (1999), Klenow and Rodriguez-Clare (1997), King and Levine (1994), or Parente and Prescott (2000). These studies assume that the aggregate production function has the Cobb-Douglas form:

$$Y = AK^{\alpha}T^{\beta}H^{1-\alpha-\beta}, \tag{5}$$

with $\alpha \simeq 1/3$, and $\beta \simeq 0$. This formulation of the production function was popularized by Solow (1957) and Denison (1967) in their studies of industrialized countries. This function ignores land as a factor of production, which may be harmless when studying industrialized countries, and implies that the labor share of income is constant at around 2/3 –a property consistent with the US experience. This function is then used to compute Solow residuals as

$$A = \frac{Y}{K^{\alpha}T^{\beta}H^{1-\alpha-\beta}}. \tag{6}$$

A limitation of (5) for cross-country comparisons is that it cannot describe well the production possibilities of agricultural countries, in which land plays a more central role than capital. For those countries, (5) probably captures well the nonagricultural sector, but not the agricultural sector. According to Proposition 1, the aggregate production function of economies with some agriculture is better described by (3) rather than (5).

At this point, it seems natural to make some assumptions to guarantee that (3) coincides with (5) for countries with almost no agriculture. This would make (3) consistent with extensive growth accounting literature that regards (5) as a satisfactory description of industrialized countries. This consistency is guaranteed by choosing the nonagriculture as the reference sector, and by assuming that the nonagricultural production function is given by (5). Under these conditions, (3) can be written as

$$Y = A_n \cdot Z_n \cdot K^{\alpha} T^{\beta} H^{1-\alpha-\beta}. \tag{7}$$

Notice that according to (4), $Z_n = 1$ for a country that allocate all its factors in the nonagricultural sector. Thus, for those countries (3) and (5) provide the same representation. Now, substituting (7) into (6), it follows that standard Solow residuals satisfy

$$A = A_n \cdot Z_n \left(k, t; B \right). \tag{8}$$

This equation provides two main insights. First, Solow residuals are a re-scaled version of nonagricultural TFPs. Second, the size of the re-scaling, Z_n, is not identical for all countries. It depends on the factor endowments of each country. The intuition from Figure 2 suggests that Z_n is larger for poorer countries than rich countries, and therefore that Solow residuals underestimate underlying productivity differences between rich and poor countries in the nonagricultural sector. This results from the fact that Solow residuals treat the gains from diversification as higher productivity. These gains, however, may not be associated to intrinsic productivity (TFP) differences across sectors, but only to differences in factor endowments.

The analysis above does not provide a connection between standard Solow residuals and *agricultural* TFPs. We can establish a relationship between Solow residuals and nonagricultural TFP just because standard computations use the nonagricultural technology as the common aggregate technology across countries. Since we cannot follow a similar procedure to compare Solow residuals and agricultural TFP, we turn to the data.

2.4 Quantitative Assessment

We now provide a quantitative assessment of the model. For this purpose we use 1988 data for a cross-section of 107 countries provided by Hall and Jones (1999) (see Table A1). Hall and Jones provide data on PPP output per worker from the Penn World Tables (PWT) 5.6, a measure of aggregate capital K constructed with investment data from the PWT, and a measure of average human capital in each country, h. Aggregate human capital satisfies $H = hL$.[4]

[4]Hall and Jones' (1999) data is available electronically at http:// emlab.berkely.edu/ users/ chad/ HallJones400.asc. On this data set, capital per worker is built with the perpetual inventory method using investment

We complete Hall and Jones' cross-section by using data on arable land T, and labor force in agriculture L_a available from the World Bank.[5] Finally, we compute sectoral output p_aY_a and p_nY_n by using PPP output per worker from the PWT combined with the percentages of agriculture and nonagriculture on total GDP at domestic prices from the World Bank.[6] Ideally, as assumed in the solution of the planner's problem (1), prices p_a and p_n should be "world prices" common to all countries. However, there is no available data for such prices.[7]

Due to the lack of data on sectoral allocation of factors, we use the model to compute K_a, K_n, T_a, T_n, H_a and H_n.[8] They can be obtained from the following efficiency conditions and resource constraints:

$$\alpha_n^K \frac{p_nY_n}{K_n} = \alpha_a^K \frac{p_aY_a}{K_a}; \qquad K_n + K_a = K;$$

$$\alpha_n^T \frac{p_nY_n}{T_n} = \alpha_a^T \frac{p_aY_a}{T_a}; \qquad T_n + T_a = T;$$

$$\alpha_n^H \frac{p_nY_n}{H_n} = \alpha_a^H \frac{p_aY_a}{H_a}; \qquad H_n + H_a = H.$$

Given a specific set of inputs shares, α_i^f, the allocations can be readily computed. Finally, Z_n is obtained using equation (4).

We now consider two scenarios. For the first scenario, assume as most accounting exercises (e.g., Hall and Jones, 1999) that labor share is 2/3 for all countries. This requires setting $\alpha_a^H = \alpha_n^H = 0.66$. This assumption is controversial and we relax it below. Moreover, suppose that agriculture is "land-labor intensive" and nonagriculture is "capital-labor intensive". This requires setting $\alpha_a^K = \alpha_n^T = 0$.[9] By residue, $\alpha_a^T = \alpha_n^K = 0.33$. The perception of agriculture as highly

series from PWT 5.6. In addition, years of schooling are taken from Barro and Lee (1993) or imputed by Hall and Jones for certain countries.

[5]Hall and Jones' original data set contains 127 countries, but the addition of agricultural variables reduces the sample to 107 countries.

[6]Gollin, Parente and Rogerson (2004) follow the same procedure. As they point out, since the percentages of agriculture and nonagriculture are based on domestic prices, this procedure does not correct for differences in relative prices between agriculture and nonagriculture across countries.

[7]FAO has constructed a world agricultural price index for 1985 measured at producer prices. The caveat is that it is not possible to combine FAO's measure of PPP agricultural GDP with total PPP GDP from PWT in order to construct nonagricultural GDP at PPP prices, because PWT data is measured at consumer prices. Moreover, as pointed out by Gollin, Parente and Rogerson (2004), the FAO data implies a extremely large reduction of agriculture as a percentage of GDP in poor countries. This makes agricultural productivity unrealistically low in these countries.

One other reason to avoid FAO data is that domestic prices are the relevant ones for rural-urban migration decisions, and for assessing the existence of a wage gap. This favors the use of World Bank data on percentages of agriculture and nonagriculture in GDP at domestic prices.

[8]Larson *et al.* (2000) provide estimates of agricultural capital stocks for a limited set of countries, and in domestic prices rather than PPP prices. To the extent or our knowledge, no data on allocation of human capital exist. We provide estimates below.

[9]In practice we make α_a^K and α_n^T close to zero, but not strictly zero, to preserve the interior solution implicit in

land-labor intensive is intended to describe agricultural technologies in poor countries, although it may not describe well agriculture in rich countries. This is a reasonable choice because agriculture is relatively more important in poor countries, so that the assumption allows to better describe technologies available for poor countries without distorting much the results for rich countries.

Figure 3 portrays the corresponding Z_n relative to the US in 1988 at different levels of income (series are reported in Table A.1). Z_n measures both the gains from diversification, and also the difference between Solow residuals and nonagricultural TFP. The figure supports two main conclusions. First, it confirms the intuition from Figure 2 that Z_n is larger in poor than in rich countries. For example, Z_n is around 1.4 for Somalia. This means that the technological gap between Somalia and US in nonagriculture is 40% larger than what is implied by Solow residuals. For the other very poor countries, the size of this overestimation ranges between 10 and 30%. As consequence, the dispersion of nonagricultural TFPs is larger than the dispersion of Solow residuals. The second conclusion from Figure 3 is that Z_n quickly decreases with the level of income, and for most countries outside the poorest range, it is not larger than 10%. Thus, it is mostly the very poor countries the ones that are poorly portrayed in standard accounting exercises.

Consider now a second scenario that relaxes the assumption of an equal labor share in agriculture and nonagriculture. On this issue, Gollin (2002) reports that in most countries, regardless of their level of development, $\alpha_a^H < \alpha_n^H$. For instance, for the US in 1992, α_a^H was around 0.25 while α_n^H was around 0.7. Although Gollin finds that, once labor income is corrected to reflect self-employment revenues, labor shares at the aggregate level are about the same across countries, there is no knowledge of whether the same would occur at the sectoral level. We find that if $\alpha_a^H = 0.3$ and $\alpha_a^T = 0.69$, then Z_n is significantly larger than in the first scenario (see values reported in Table A.1). Specifically, it is more than 80% in Somalia and between 10 and 60% for most other poorer countries.

Our exercises suggest that very poor countries are poorly represented in standard models that abstract from land and agriculture. Moreover, the conclusion that nonagricultural TFPs are more disperse than Solow residuals has important practical implications. Consider for example the case of Somalia. Our finding that Somalia's nonagricultural TFP is significantly smaller than aggregate TFP implies that most of Somalia's poverty will remain even if Somalia transforms itself into a

equation (3).

more urbanized (nonagricultural) economy.

Although it is not possible to establish a theoretical link between agricultural TFP and Solow residuals, we can compare the Solow residual and the agricultural TFPs derived from the model. Table 1 summarizes the cross-country variance of sectoral TFPs and Solow residuals for different technologies in the agricultural sector. For the nonagricultural sector we use the standard values of $\alpha_n^H = 2/3$ and $\alpha_n^K = 1/3$. The first row shows that Solow residuals properly assess productivity differences when factor shares are equal across sectors. The second and third rows consider the case in which labor share is the same in agriculture and nonagriculture ($\alpha_a^H = \alpha_n^H = 2/3$) in combination with two different values for land share in agriculture. The last two rows correspond to the case in which labor share is lower in agriculture than in nonagriculture, and land share is increasingly higher, up to $\alpha_a^T = 0.69$. As the table shows, agricultural TFP is even more disperse than its nonagricultural counterpart. In particular, the larger the share of land in agriculture, the larger the variance of agricultural TFP. For instance, when land share is $\alpha_a^T = 0.69$, the variance of (log) agricultural TFP is 0.79, compared with 0.34 of nonagricultural TFP and 0.24 of Solow residuals.

Other studies in the literature (e.g., Gollin, Parente and Rogerson, 2004; Restuccia, Yang, and Zhu, 2003; and Caselli, 2004) have documented the large cross-country dispersion of labor productivity in agriculture. For instance, using a sample of 80 countries in 1985, Caselli (2004) documents that the log-variance of labor productivity in agriculture is 2.15, while it is 0.33 in nonagriculture and 1.18 for the aggregate. These numbers suggest that the aggregate log-variance corresponds to a weighted average of the sectoral variances. In contrast, Table 1 focuses on sectoral versus aggregate TFPs and shows that the dispersion of *both* agricultural and nonagricultural TFP is larger than the dispersion of standard Solow residuals. This result implies that the dispersion of standard Solow residuals is *not* a weighted average of sectoral TFP dispersions.

2.5 Levels Accounting

2.5.1 Methodology

In this section we compare development accounting exercises using the traditional one-sector model and our benchmark two-sector model. Traditional accounting exercises based on equation (5) decompose the cross-country variance of log output per worker $log(Y/L)$ into factors of production K, H, and T, and total factor productivity A. Following Klenow and Rodríguez-Clare (1997) and

Hall and Jones (1999), (5) can be rewritten as

$$y \equiv \frac{Y}{L} = \widetilde{A} \cdot \widetilde{X} \tag{9}$$

where $\widetilde{X} \equiv (K/Y)^{\frac{\alpha}{1-\alpha-\beta}} (T/Y)^{\frac{\beta}{1-\alpha-\beta}} h$ is referred to as factor intensity, and $\widetilde{A} \equiv A^{\frac{1}{1-\alpha-\beta}}$ is referred to as the TFP component. This reformulation of the production function imputes part of the differences in capital stocks to differences in TFP, an imputation that arises naturally in models of exogenous TFP. The analogous formulation for (7), the production function in our two-sector model is

$$y \equiv \frac{Y}{L} = \overline{A} \cdot \overline{X} \cdot \overline{Z}. \tag{10}$$

where $\overline{X} \equiv (K/Y)^{\alpha_n^K/\alpha_n^H} (T/Y)^{\alpha_n^T/\alpha_n^H} h$ is the factor intensity component, $\overline{A} \equiv A_n^{1/\alpha_n^H}$ is the TFP component, and $\overline{Z} \equiv Z_n^{1/\alpha_n^H}$ is the diversification (adjustment) component. Equation (9) is a special case of (10) in which factor shares are equal across sectors. Following Klenow and Rodríguez-Clare (1997), the contributions of factors, TFP, and the diversification components to output dispersion can be defined as:

$$\Phi_{\overline{X}} = \frac{cov\left(\ln y, \ln \overline{X}\right)}{var\left(\ln y\right)}; \quad \Phi_{\overline{A}} = \frac{cov\left(\ln y, \ln \overline{A}\right)}{var\left(\ln y\right)}; \quad \Phi_{\overline{Z}} = \frac{cov\left(\ln y, \ln \overline{Z}\right)}{var\left(\ln y\right)}.$$

where $\Phi_{\overline{X}} + \Phi_{\overline{A}} + \Phi_{\overline{Z}} = 1$.

As Figure 5 shows, $\overline{Z}$ is larger for poorer countries, the ones with larger agricultural sectors. As a result, $\Phi_{\overline{Z}}$ is negative. According to equation (8), standard accounting exercises fully incorporate the diversification component $\overline{Z}$, as part of TFP. This means that these exercises implicitly define the contribution of TFP as $\Phi_{\overline{A}} + \Phi_{\overline{Z}}$. Since $\Phi_{\overline{Z}}$ is negative, this definition downplays the role of TFP. A more accurate definition of the contributions of TFP and factors needs to assign part of $\Phi_{\overline{Z}}$ to factors. This is clear from equation (4), which states that the degree of diversification Z_n, depends in part on the factor endowments of the economy.

Since it is unclear how to exactly assign $\Phi_{\overline{Z}}$, we divide $\Phi_{\overline{Z}}$ equally between TFP and factors components.[10] Specifically, we define the contributions of factors, Φ_X, and TFP, Φ_A, as

$$\Phi_X = \Phi_{\overline{X}} + \Phi_{\overline{Z}}/2; \quad \Phi_A = \Phi_{\overline{A}} + \Phi_{\overline{Z}}/2.$$

2.5.2 Results for Benchmark Model

Table 2 reports the percentage contribution to world income variance of factors and TFP for our benchmark model and for different parameter values. The table assumes parameter values for the nonagricultural sector of $\alpha_n^K = 0.33$, $\alpha_n^H = 0.66$, and $\alpha_n^T = 0.01$. As argued in Section 3.3, these parameter values guarantee that rich countries are properly portrayed in the two-sector model. The first row of Table 2 reproduces the standard result that implicitly assumes identical production functions across sectors. According to this one-sector model, factor intensity X accounts for 38% of output per worker variation, while the other 62% is attributed to TFP.

Table 2 also reports accounting results for parameters values in which land becomes increasingly important in the production of agriculture. The land share initially increases at the expense of the capital share (rows second and third) and then at the expense of the labor share (rows fourth and fifth). All cases in the table are potentially relevant, given the cross-country evidence about factor shares. Under the scenarios presented in the table, the percentage contribution of the TFP increases systematically with the share of land up to a value of 70%.

The results in Table 2 confirm Caselli's (2004) finding that sectoral considerations increase the role of TFP in accounting for cross-country income inequality, although the quantitative increase is relatively small. Our theoretical model allow us to provide an explanation for these results. TFP differences are larger than previously thought. The relative small increase in the contribution of TFP is due to the fact that for most countries the adjustment factor Z_n is small, and it is only significant for a relative small number of very poor countries (see Figure 3). This would suggest that considering differences in sectoral composition of output across countries is not important for understanding cross-country income dispersion. Next section shows that this is actually not the case.

[10]Thus, we follow Klenow and Rodriguez-Clare's methodology of spliting the covariance term equally between factors of production and TFP.

3 The Wage Gap

This section studies the implications of the benchmark model regarding labor productivity gaps between agriculture and nonagriculture and extends the baseline model. Gollin, Parente & Rogerson (2004) and Restuccia, Yang & Zhu (2003), among others, have recently documented that wages, approximated by the average product of labor, are generally lower in agriculture than in nonagriculture, more so in poorer countries. Figure 1 documents this regularity using our database. It shows the average productivity of labor in nonagriculture relative to agriculture for 1988. According to the figure, the productivity of labor in nonagriculture is up to 15 to 25 times larger than its agricultural counterpart in the poorest countries. However, for countries with GDP per worker above \$10,000 this ratio is below 5, and on average below 3.

Denote by w_{gap} the ratio of labor productivity in nonagriculture relative to agriculture:

$$w_{gap} \equiv \frac{p_n Y_n / L_n}{p_a Y_a / L_a}. \tag{11}$$

The benchmark model assumes efficient allocation of human capital, or

$$\alpha_a^H \frac{p_a Y_a}{H_a} = \alpha_n^H \frac{p_n Y_n}{H_n}. \tag{12}$$

Defining $h_i \equiv H_i / L_i$ to be the average average level of human capital per worker in sector $i = \{a, n\}$, the last two equations imply that

$$w_{gap} = \frac{h_n}{h_a} \frac{\alpha_a^H}{\alpha_n^H}. \tag{13}$$

Thus, in our benchmark model the wage gap is accounted for by differences in human capital across sectors and/or by differences in the human capital shares in the sectoral production functions. Notice that this wage gap is *not* explained by differences in TFP across sectors. If $\alpha_a^H = \alpha_n^H$, then our benchmark model accounts for the wage gap in terms of human capital differences across sectors. This explanation has previously been advanced by Caselli and Coleman (2001), as well as Lucas (2004), in the context of the wage gap between rural and urban areas. According to this viewpoint, rural workers do not move to cities because their low human capital precludes any important wage gains. Notice that the case $\alpha_a^H = \alpha_n^H$ provides a lower bound for h_n/h_a in our model because, if anything, the data documented above suggest that $\alpha_a^H < \alpha_n^H$.

3.1 Years of Schooling and the Wage Gap

In order to assess the extent to which differences in educational attainment explain the wage gap, we use available information from UNESCO to construct series of schooling for rural and urban areas for a cross section of countries (see Appendix B for details). The data are scattered in time and space (see Table A.2), but the available information reveals a strong relationship between average years of schooling in a country and average years of schooling in its rural and urban areas (see Figure A1). We exploit this relationship to extrapolate data for our full cross-section of countries in 1988, as explained in Appendix B. We then compute human capital series for agriculture and nonagriculture, h_a^s and h_n^s, using the Mincer equations employed by Hall and Jones (1999). These human capital series are constructed under the assumptions that both the quality of education and the returns to schooling are identical across sectors and countries. Urban and rural human capital series are reported in Table A.3 for our sample of countries in 1988.[11]

Figure 4 shows the wage gap that remains after controlling for differences in schooling, $w_{gap} \cdot h_a^s/h_n^s$ (under the assumption $\alpha_a^H = \alpha_n^H$). If the full gap were explained by differences in years of schooling, this ratio would be equal to 1. However, Figure 4 shows that most of the wage gap (shown in Figure 1) remains after controlling for schooling differences. In fact, the magnitude of the gap not accounted for by years of education is up to 10 or 18. However, for countries with GDP per worker above $10,000 the unexplained wage gap is below 4, and on average below 2. In conclusion, differences in years of education across rural and urban areas are not the main explanation for the rural-urban wage gap. This finding compelled us to extent the benchmark model to better account for the wage gap.

We consider two additional possibilities. The first one is that there are economic costs associated with rural-urban migration not modeled in our benchmark framework. The second possibility is that the *quality* of human capital is not the same across rural and urban areas. In particular, we impute the fraction of the wage gap not accounted for by schooling or migration costs as quality differences in human capital across sectors. This procedure allows us to construct new quality-

[11]The most recent version of Vollrath (2005) adopts a methodology similar to ours but uses data from Timmer (2002). The correlation between our rural and urban human capital series and Vollrath's implied extrapolation for 1988 is 0.996.

adjusted sectoral and aggregate series of human capital. We can then compare the aggregate series of quality-adjusted human capital with related estimates from existing studies, in particular Manuelli and Seshadri (2004), in order to asses whether differences in the quality of human capital across sectors provide a quantitatively reasonable explanation for the observed wage gap.

3.2 Migration Costs

Consider the following dynamic version of the Harris and Todaro (1970) migration model. An infinitely-lived individual has two options: stay in the rural area and earn a wage w_a permanently or migrate. Her lifetime utility if staying is $V_a = u(w_a)/(1-\beta)$, where $u(.)$ is a per-period utility function and β is the discount factor. An individual who migrates is unemployed for one period, and may find a job next period with probability π, where $1-\pi$ is the unemployment rate. While unemployed, the individual earns $w_{\min}$, a "wage" obtained by working in an outside option, say in the informal sector. To prevent all individuals moving to the city, assume that $w_{\min} < w_a$. If employed, the individual earns a permanent wage of w_n. The lifetime utility of an individual with a city job is $V_n = u(w_n)/(1-\beta)$. The lifetime utility of an unemployed worker is $W = u(w_{\min}) + \beta(1-\pi)W + \beta\pi V_n$, which can be written as

$$W = \frac{1}{1-\beta(1-\pi)}\left[u(w_{\min}) + \frac{\beta\pi}{1-\beta}u(w_n)\right].$$

In equilibrium, wages must be such that individuals are indifferent between moving and staying. Thus, $V_a = u(w_{\min}) + \beta(1-\pi)W + \beta\pi V_n$. Substituting for W into this expression yields $[1-\beta(1-\pi)]\,u(w_a) = (1-\beta)\,u(w_{\min}) + \beta\pi u(w_n)$. Finally, assuming logarithmic utility produces $(1-\beta)\ln w_a = (1-\beta)\ln w_{\min} + \beta\pi(\ln w_n - \ln w_a)$, or

$$\frac{w_n}{w_a} = \left(\frac{w_a}{w_{\min}}\right)^{\frac{1-\beta}{\beta\pi}}.$$

The equation above describes the wage gap w_n/w_a that one would observe if all workers in the economy were identical, in particular regarding their human capitals. According to the equation, the rural-urban wage gap depends negatively on β and positively on the rural-informal wedge, $w_a/w_{\min}$, and on π. Thus, a higher rate of unemployment increases the wage gap but patience reduces the wage gap. Since β is typically considered to be close to 1, the expression above suggests that only a small wage gap must be observed in equilibrium. For example, for a standard value of $\beta = 0.95$, an unemployment rate of 15%, and a ratio of agricultural wage to informal wage of 10 (or $w_a/w_{\min} = 10$), the wage gap is only 15% ($w_n/w_a = 1.15$). Doubling the unemployment rate would increase the gap to 18%, and doubling the $w_a/w_{\min}$ ratio would increase the gap to 20%. These gaps are significant but far from explaining the evidence in Figure 1 or Figure 4.

This simple migration model contains the main mechanism proposed by Harris and Todaro (1970) to explain rural-urban migration, although in a dynamic setting. The fact that individuals significantly value their future is the key reason why the model can only predict relatively small rural-urban wage gaps. Additional migration costs, such as transportation costs or set up costs, can be introduced but they still would have only a very limited effect in generating large wage gaps because these costs are paid only once.

3.3 Quality of Human Capital

Another explanation for the wage gap is that the average level of human capital differs across rural and urban areas due to differences in *quality*. We think of these quality differences as embodied in the worker. In particular, it is plausible that human capital in poor countries (where most workers are in rural areas) is lower than what is implied by Mincerian equations due, for example, to poor quality of schooling and low parental human capital. Denote q_a the quality of human capital in agriculture (rural areas). Normalizing the quality in nonagriculture (urban areas) to 1, i.e. $q_n = 1$, a reasonable conjecture is that $q_a < 1$, i.e., that the quality of human capital is lower in rural areas.[12] Incorporating differences in human capital quality into the migration model above implies a wage gap of:

$$w_{gap} = \left(\frac{w_a}{w_{\min}}\right)^{\frac{1-\beta}{\beta\pi}} \frac{h_n^s}{h_a^s}\frac{1}{q_a}. \tag{14}$$

3.4 The Wage Gap and Aggregate Human Capital

We now use equation (14) to back up values of q_a for different countries. We have information about w_{gap} from the data (see Figure 1), and we constructed series of human capital for agriculture and non-agriculture, h_n^s and h_a^s (see Table A.3). To calibrate the gap due to migration costs,

[12] $q_n = 1$ also implies that the quality of urban human capital is identical across countries. The wage gap could also be explained by $q_n > 1$ in poor countries. However, this alternative would have the unplausible implication that the quality of urban human capital is better in poor countries than in rich countries. Assuming $q_n < 1$ would only strengthen our results.

$(w_a/w_{\min})^{(1-\beta)/(\beta\pi)}$, we assume that $q_a = 1$ for the US. This implies $(w_a/w_{\min})^{(1-\beta)/(\beta\pi)} = 1.46$ so that migration costs account for a 46% wage gap, a value rather large given our simulations above, but conservative for our purposes: reducing migration costs would strengthen our results below. Given these assumptions, equation (14) can be used to find q_a for each country.

Finally, the aggregate level of human capital in each country is defined as

$$H = q_a h_a^s L_a + h_n^s L_n. \tag{15}$$

The novelty of our human capital estimates is that they are constructed using sectoral schooling information and wage gap information to assess quality differences. Figure 5 compares our quality-adjusted series of human capital with the unadjusted ones. Both series are very similar for rich countries but they are significantly different for poor countries. The data are reported in Table A.4.

To assess how plausible our quality-adjusted series of human capital are, Figure 6 plots the ratios of human capital to output for both adjusted and unadjusted stocks. According to the unadjusted estimates, this ratio decreases significantly with income. This is a consequence of the concavity of Mincer returns to schooling. A rather counterintuitive implication of these estimates is that the 20 poorest countries in the sample employ on average 11.3 times more human capital per unit of output than the US. Our quality-adjusted estimates still produce a decreasing ratio of human capital to output but the 20 poorest countries only employ 5 times more human capital per unit of output than the US.

Our estimates of human capital are also consistent with those of Manuelli and Seshadri (2004). For example, consider the following comparison between the US and Zambia. Zambia is one of the countries in the lowest quintile of the output per worker distribution, it has a high wage gap of around 15, and relatively low average years of schooling of 4.4. Based only on schooling, human capital in the rural areas of the US is around 1.9 times higher than in the rural areas of Zambia. In contrast, adjusting for quality, it is 16 times higher. This implies that the quality of rural workers in the US is around 8.5 times higher than their counterparts in Zambia. What does this imply for *average* (aggregate) human capital? Based only on schooling, average (rural and urban) human capital in the US is around 1.9 times that of Zambia, but adjusting for quality makes it around 5.3 times higher. This implies that the *average quality* of human capital in the US is around 2.8 times higher than in Zambia. It turns out that this number is not high compared to the one suggested by Manuelli and Seshadri (2004) in the context of a different model –they do not consider a sectoral model with agriculture, but a model of endogenous human capital accumulation. According to their model, quality of human capital in the US is around 5 times higher than in a country in the lowest decile of their sample (with average years of schooling of 2).[13]

In sum, our hypothesis that the wage gap is accounted for by migration costs, as well as differences in schooling and the quality of human capital seems quantitatively reasonable. This is so because our implied aggregate differences in quality-adjusted human capital across rich and poor countries is in line with estimates from existing studies.

3.5 Revisiting Levels Accounting

This section revisits the levels accounting exercise described in Section 2 using the quality-adjusted series of human capital constructed above. Section 2 concluded that explicitly incorporating the agricultural sector in our benchmark model increases the role of TFP in explaining cross-country income differences, although the quantitative increase is relatively small (see Table 2). Table 3 employes the same methodology as Table 2 but uses quality-adjusted human capital series. Comparing the last two columns of Table 2 with the last columns of Table 3, it is clear that the levels accounting results are significantly affected. Factors of production systematically account for a larger bulk of the cross-country income dispersion than TFP when human capital series are adjusted to reflect sectoral differences in schooling, quality, and migration costs. For example, when technologies are identical across sectors (first rows in both tables), the contribution of TFP falls from 62% to 34%, while it falls from 70% to 45% when agriculture is highly intensive in land (last rows of the tables). For the intermediate and plausible case in which both sectors share the same labor intensity of 66%, the contribution of TFP falls from 66% to 40%.

The intuition for these result is as follows. Controlling for years of schooling and migration costs, rural workers in poor countries seem to have much lower quality of human capital than their city counterparts. Moreover, the quality of human capital in cities of poor countries is likely to be either lower or similar to rich countries. These two observations together mean that human capital

[13]In Manuelli and Seshadri (2004), quality of human capital is a function of wages and demographics (i.e., retirement age and age of working population, which are assumed to be orthogonal to TFP). In addition, and similar to our model, quality of human capital is embodied in workers.

is much lower in poor countries than what is currently estimated by many studies, which abstract from differences in quality across countries and across sectors. As a result, the dispersion of human capital around the world increases substantially, and the percentage contribution of factors to the world income dispersion is significantly higher.

4 Concluding Comments

This paper studies how the explicit consideration of sectoral differences between agriculture and nonagriculture affects our understanding of the sources of cross-country income differences. Although the data clearly support differences in sectoral composition across countries, and the intensive use of land in agriculture suggests sectoral differences in production technologies across sectors, the mainstream literature in development accounting has traditionally abstracted from these issues. The main contribution of this paper has been to show analytically and numerically that sectoral differences matter substantially for understanding the sources of cross-country income differences.

Our first contribution is to show that Solow residuals provide a biased picture of the underlying technological differences across countries. To this effect, we show analytically and numerically that the dispersion of nonagricultural TFP is larger than the dispersion of Solow residuals. Moreover, we show numerically that the dispersion of agricultural TFP is larger than the dispersion of Solow residuals. These results are robust to different technology parameters and suggest that the overall contribution of TFP differences to world income dispersion must be larger than previously thought.

However, our second main finding turns out to be quantitatively more relevant. We find that properly accounting for the large observed wage gap between agriculture and nonagriculture overturns well-established results. In particular, we find that large wage gaps are not explained by differences in schooling or migration costs, but rather seem to be explained by particularly low quality of human capital in rural areas. This finding implies that differences in factors of production rather than differences in TFP explain most of the dispersion in output per worker across countries.

Our analysis makes clear the importance of considering two-sector models rather than single-sector models for the study of the sources of cross-country income differences. Moreover, it calls for more research on measuring the quality of human capital, particularly in rural areas in poor countries.

APPENDIX

A Proof of Proposition 1

Let $k_i = K_i/H_i$ and $t_i = T_i/H_i$ for $i = a, n$, and $h_a = H_a/H$. These five unknowns can be solved for using the following system of five equation that includes three first-order conditions and two resource constraints. We can write the first-order conditions as

$$\begin{aligned} F_K^a\left(k_a^*, t_a^*, 1\right) &= BF_K^a\left(k_n^*, t_n^*, 1\right) \\ F_T^a\left(k_a^*, t_a^*, 1\right) &= BF_T^n\left(k_n^*, t_n^*, 1\right) \\ F_H^a\left(k_a^*, t_a^*, 1\right) &= BF_H^n\left(k_n^*, t_n^*, 1\right) \end{aligned}$$

and the resource constraints as

$$k_a^* h_a^* + k_n^*\left(1 - h_a^*\right) = k$$

$$t_a^* h_a^* + t_n^*\left(1 - h_a^*\right) = t$$

where the superscript * denotes the efficient allocation. The system of equations above shows, as Lemma 1 indicates, that the optimal allocation rules of capital and land per unit of effective labor in sectors a and n depend only on the ratios $(k,\ t;\ B)$ but not on the exact levels $(K, T, H; \overrightarrow{A})$. More specifically, for the Cobb-Douglas case we have

$$\begin{aligned} \alpha_a^K k_a^{*\alpha_a^K - 1} t_a^{*\alpha_a^T} &= B\alpha_n^K k_n^{*\alpha_n^K - 1} t_n^{*\alpha_n^T} \\ \alpha_a^T k_a^{*\alpha_a^K} t_a^{*\alpha_a^T - 1} &= B\alpha_n^T k_n^{*\alpha_n^K} t_n^{*\alpha_n^K - 1} \\ \alpha_a^H k_a^{*\alpha_a^K} t_a^{*\alpha_a^T} &= B\alpha_n^H k_n^{*\alpha_n^K} t_n^{*\alpha_n^T} \end{aligned}$$

and dividing the two first equations by the third one obtains

$$\begin{aligned} k_n^* &= \frac{\alpha_n^K}{\alpha_a^K}\frac{\alpha_a^H}{\alpha_n^H} k_a^* \\ t_n^* &= \frac{\alpha_n^T}{\alpha_a^T}\frac{\alpha_a^H}{\alpha_n^H} t_a^*. \end{aligned}$$

Using these results one can write

$$\alpha_a^H k_a^{*\alpha_a^K - \alpha_n^K} t_a^{*\alpha_a^T - \alpha_n^T} = B\alpha_n^H \left(\frac{\alpha_n^K}{\alpha_n^H}\frac{\alpha_a^H}{\alpha_a^K}\right)^{\alpha_n^K} \left(\frac{\alpha_n^T}{\alpha_n^H}\frac{\alpha_a^H}{\alpha_a^T}\right)^{\alpha_n^T}$$

$$k_a^* = \frac{k}{h_a^* + \frac{\alpha_n^K}{\alpha_a^K}\frac{\alpha_a^H}{\alpha_n^H}\left(1 - h_a^*\right)}$$

$$t_a^* = \frac{t}{h_a^* + \frac{\alpha_n^T}{\alpha_a^T}\frac{\alpha_a^H}{\alpha_n^H}\left(1 - h_a^*\right)}$$

and substituting the latter two equations into the first, one can obtain the following non-linear function to solve for h_a^*[14]

$$\left(h_a^* + \frac{\alpha_n^K}{\alpha_a^K}\frac{\alpha_a^H}{\alpha_n^H}(1-h_a^*)\right)^{\alpha_n^K-\alpha_a^K}\left(h_a^* + \frac{\alpha_n^T}{\alpha_a^T}\frac{\alpha_a^H}{\alpha_n^H}(1-h_a^*)\right)^{\alpha_n^T-\alpha_a^T}$$
$$= Bk_a^{*\alpha_n^K-\alpha_a^K} t_a^{*\alpha_n^T-\alpha_a^T}\frac{\alpha_n^H}{\alpha_a^H}\left(\frac{\alpha_n^K}{\alpha_a^K}\frac{\alpha_a^H}{\alpha_n^H}\right)^{\alpha_n^K}\left(\frac{\alpha_n^T}{\alpha_a^T}\frac{\alpha_a^H}{\alpha_n^H}\right)^{\alpha_n^T}.$$

The latter equation solves for h_a^*, and using previous equations one can solve for k_i, t_i. Next, it is easy to show that for any sector j, the aggregate production function can be written as

$$\begin{aligned} Y_j &= G(K,T,H;\overrightarrow{A}) \\ &= A_j F^j(K,T,H)\left[\alpha_j^K \frac{F_K^j(K_j,T_j,H_j)}{F_K^j(K,T,H)} + \alpha_j^T \frac{F_T^j(K_j,T_j,H_j)}{F_T^j(K,T,H)} + \alpha_j^H \frac{F_H^j(K_j,T_j,H_j)}{F_H^j(K,T,H)}\right] \end{aligned}$$

or

$$\begin{aligned} G(K,T,H;\overrightarrow{A}) &= A_j F^j(K,T,H) \times \\ &\left[\alpha_j^K\left(\frac{k_j}{k}\right)^{\alpha_j^K-1}\left(\frac{t_j}{t}\right)^{\alpha_j^T} + \alpha_j^T\left(\frac{k_j}{k}\right)^{\alpha_j^K}\left(\frac{t_j}{t}\right)^{\alpha_j^T-1} + \alpha_j^H\left(\frac{k_j}{k}\right)^{\alpha_j^K}\left(\frac{t_j}{t}\right)^{\alpha_j^T}\right] \end{aligned}$$

which has the form

$$Y_j = G(K,T,H) = A_j F^j(K,T,H) Z^j(k,t,B)$$

where

$$Z^j(k,t;B) = \left(\frac{k_j}{k}\right)^{\alpha_j^K}\left(\frac{t_j}{t}\right)^{\alpha_j^T}\left[\alpha_j^K\frac{k}{k_j} + \alpha_j^T\frac{t}{t_j} + \alpha_j^H\right]$$

as in Proposition 1.

B Rural and Urban Schooling

Average years of schooling in rural and urban areas is constructed using urban/rural educational attainment from UNESCO, available at http:// www.uis.unesco.org/ ev.php? ID=5234_201 & ID2=DO_TOPIC. Data are scarce: they are available for few years and countries. We use data for 52 countries (one observation per country), but extrapolate it to other countries by using linear regressions. Table A.2 shows these 52 countries and the year for which we use their data (the latest available year for each country is used). Data includes population above 25 years of age by location (rural/ urban) with: no schooling, primary incomplete and complete, secondary incomplete and

[14] A simplification of this expression obtains when $\alpha_n^K - \alpha_a^K = \alpha_a^T - \alpha_n^T$, that is, when $\alpha_n^K + \alpha_n^T = \alpha_a^T + \alpha_a^K$, which means just that $\alpha_n^H = \alpha_a^H$, a reasonable assumption. Under this simplification, there is a closed-form solution for h_a^* as follows:

$$\frac{h_a^* + \frac{\alpha_n^K}{\alpha_a^K}(1-h_a^*)}{h_a^* + \frac{\alpha_n^T}{\alpha_a^T}(1-h_a^*)} = g \equiv \left[Bk_a^{*\alpha_n^K-\alpha_a^K} t_a^{*\alpha_n^T-\alpha_a^T}\left(\frac{\alpha_n^K}{\alpha_a^K}\right)^{\alpha_n^K}\left(\frac{\alpha_n^T}{\alpha_a^T}\right)^{\alpha_n^T}\right]^{\frac{1}{\alpha_n^K-\alpha_a^K}}$$

so that,

$$h_a^* = \frac{g\frac{\alpha_n^T}{\alpha_a^T} - \frac{\alpha_n^K}{\alpha_a^K}}{1 - g + g\frac{\alpha_n^T}{\alpha_a^T} - \frac{\alpha_n^K}{\alpha_a^K}}.$$

Note that h_a^* does not depend on h. Thus, if all economies equate their capital h to the US capital stock, h_a^* is not affected. Also, h_a^* is not affected by TFP. However k and t affect h_a^*.

complete and post-secondary. Urban/rural average years of schooling are constructed by assigning 0 years of schooling to no schooling, 2.5 to primary incomplete, 5 to primary complete, 7.5 to secondary incomplete, 10 to secondary complete, and 12.5 to post-secondary. It turns out, as shown in Figure A.1, that the relationship between total schooling and each of the categories: urban U and rural R in the sample can be well approximated with linear functions. The estimated equations are

$$s_U = \underset{(10.6)}{1.432} + \underset{(30.7)}{0.89} \cdot s \qquad R^2 = 0.95,$$

$$s_R = -\underset{(-4.84)}{0.628} + \underset{(33.4)}{0.924} \cdot s \qquad R^2 = 0.95,$$

where s stands for average years of schooling, and the numbers below each estimated coefficient are t-statistics. Since s is available for the full sample of countries, the equations above can be used to generate rural/urban schooling numbers.

References

[1] Caselli, Francesco, "Accounting for Cross-Country Income Differences," *NBER Working paper* 10828 (2004).

[2] Caselli, Francesco and W. John Coleman, "The U.S. Structural Transformation and Regional Convergence: A Reinterpretation," *Journal of Political Economy*, 109 (2001), 584-616.

[3] Dalgaard, Carl-Johan and Areendam Chanda, "Dual Economies and International Total Factor Productivity Differences," Unpublished manuscript, 2003.

[4] Denison, E.F, "Why Growth Rates Differ," The Brookings Institution: Washington, D.C., 1967.

[5] Gollin, Douglas, Stephen Parente, and Richard Rogerson, "Farm Work, Home Work and International Productivity Differences," *Review of Economic Dynamics*, 7 (2004), 827-850.

[6] Gollin, Douglas, "Getting Income Shares Right," *Journal of Political Economy*, 110 (2002), 458-74.

[7] Hall, Robert E. and Charles I. Jones, "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *Quarterly Journal of Economics*, 114 (1999), 83-116.

[8] Harris J. and M. Todaro (1970). Migration, Unemployment & Development: A Two-Sector Analysis. American Economic Review, March 1970; 60(1):126-42.

[9] Hatton, D.J., and J.G. Williamson, "Integrated and Segmented Labor Markets: Thinking in Two Sectors," *Journal of Economic History, 51 (*1991), 413-25.

[10] Kannappan, Subbiah , "Urban Employment and the Labor Market in Developing Nations," *Economic Development and Cultural Change*, 33 (1985), 699-730.

[11] King, Robert and Ross Levine, "Capital fundamentalism, economic development, and economic growth." *Carnegie-Rochester Conference Series on Public Policy*, 40 (1994), 259-92.

[12] Klenow, Peter J. and Andrés Rodríguez-Clare, "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" in Ben S. Bernanke and Julio J. Rotemberg, eds., *NBER macroeconomics annual 1997*. Cambridge, MA: MIT Press, 1997, 73-103.

[13] Lucas, Robert E, "Life Earnings and Rural-Urban Migration," *Journal of Political Economy*, 112 (Part 2, 2004), S29-S59.

[14] Magnac, T., "Segmented or Competitive Labor Markets?," *Econometrica*, 59 (1991), 165-181.

[15] Manuelli, Rodolfo and Ananth Seshadri, "Human Capital and the Wealth of Nations," Unpublished manuscript (2004).

[16] Parente, Stephen and Edward Prescott, *Barriers to Riches* Cambridge, MA: MIT Press, 2000.

[17] Pratap, Sangeeta and Erwan Quintin, "Are Labor Markets Segmented in Argentina?: A Semiparametric Approach," Unpublished manuscript (2003).

[18] Prescott, Edward, "Needed: A Theory of Total Factor Productivity," *International Economic Review*, 39 (1998), 525-551.

[19] Restuccia, Diego, Dennis Tao Yang, and Xiaodong Zhu, "Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis," Unpublished manuscript (2003).

[20] Tannen, Michael, "Labor Markets in Northeast Brazil: Does the Dual Market Model Apply?," *Economic Development and Cultural Change*, 39 (1991).

[21] Timmer, Peter, "Agriculture and Economic Development," in B. Gardner and G. Rausser eds., *Handbook of Agricultural Economics*, Vol. 2, Part 1 (2002), 1487-1546.

[22] Vollrath, Dietrich, "How Important are Dual Economy Effects for Aggregate Productivity?," Manuscript (2005).

Figure

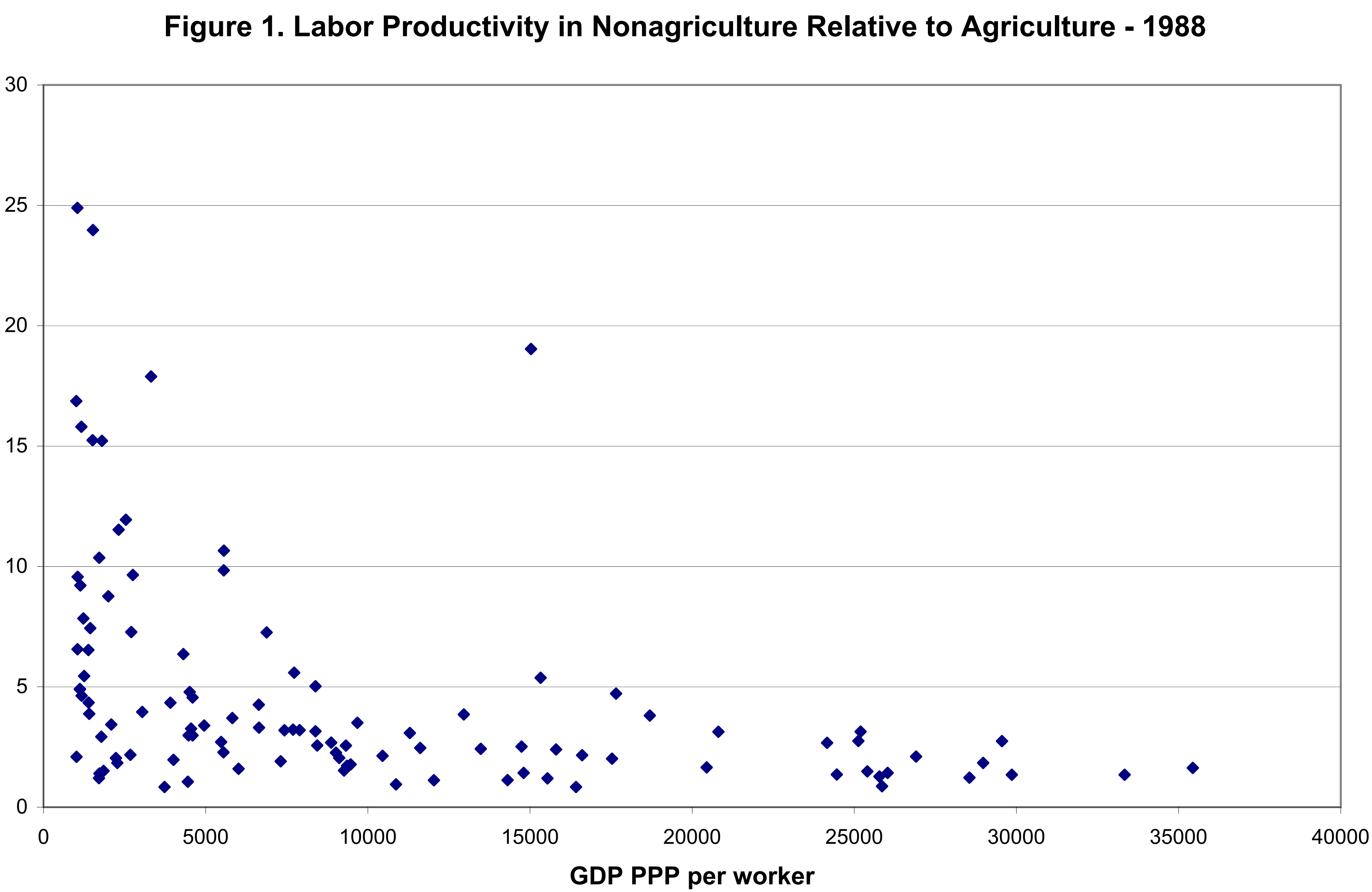
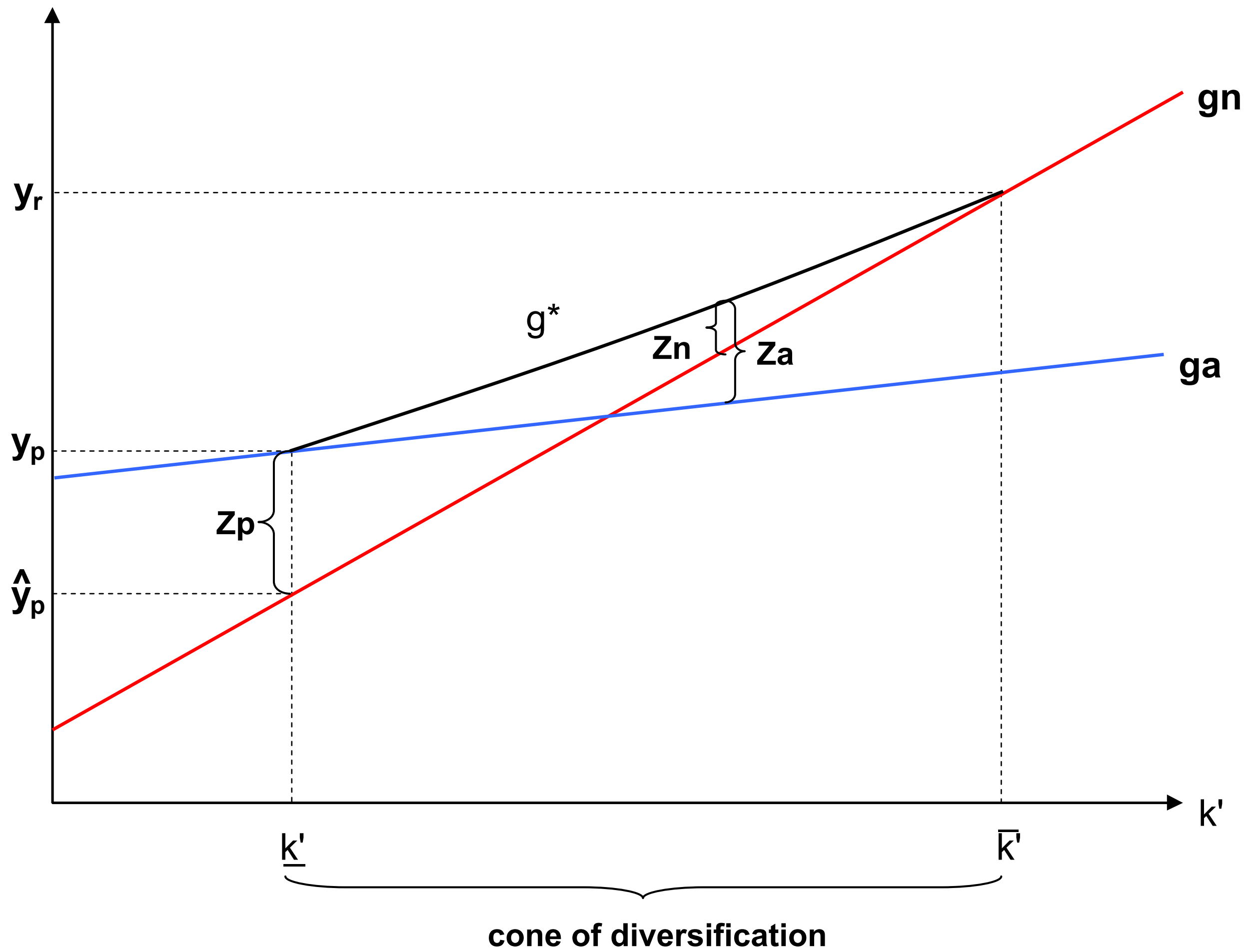


Figure 1. Labor Productivity in Nonagriculture Relative to Agriculture - 1988
30
25
20
15
10
5
0
0
5000
10000
15000
20000
25000
30000
35000
40000
GDP PPP per worker

Figure 2. Sectoral and Aggregate Production Functions



Figure

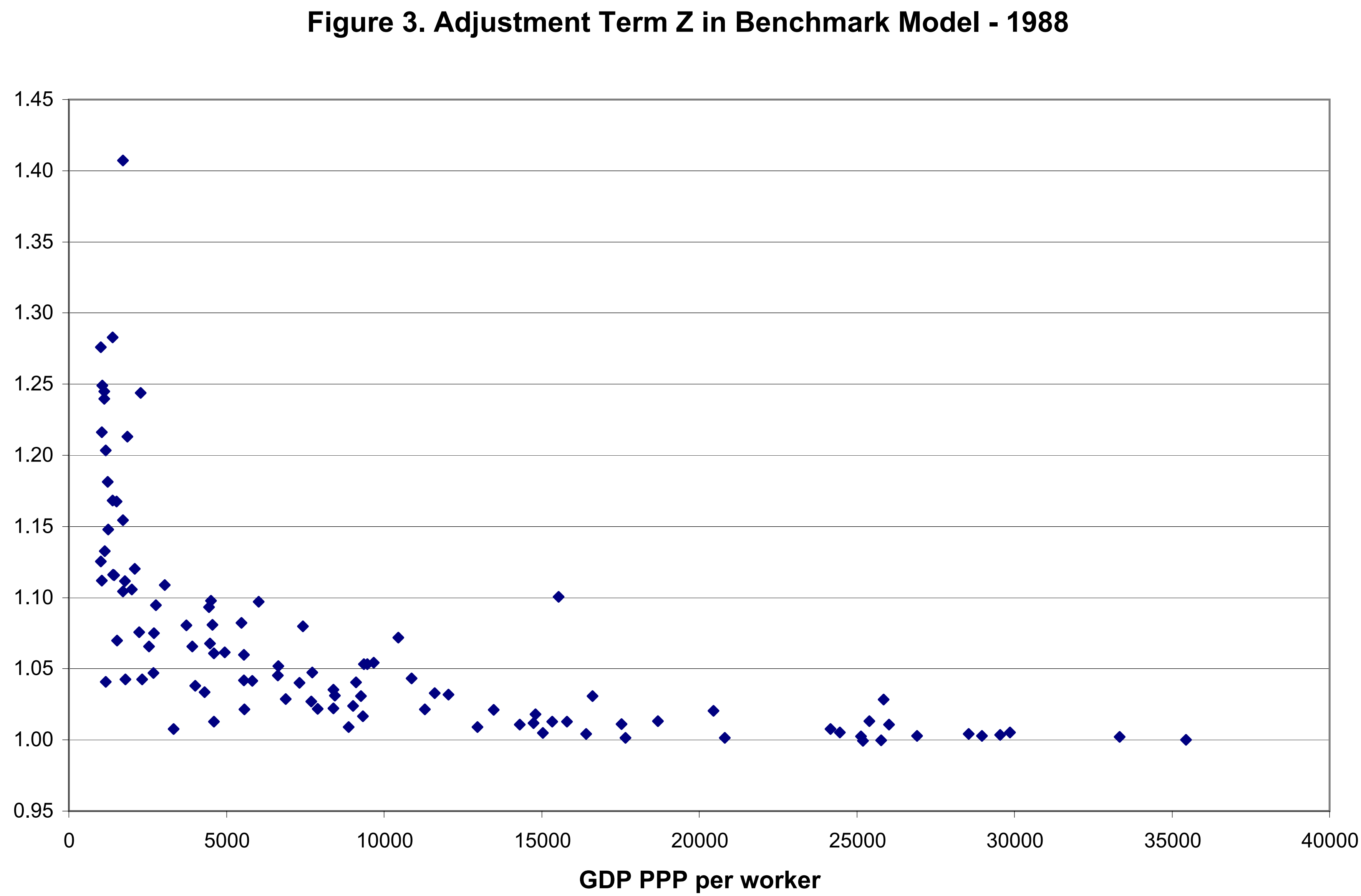


Figure 3. Adjustment Term Z in Benchmark Model - 1988
1.45
1.40
1.35
1.30
1.25
1.20
1.15
1.10
1.05
1.00
0.95
0
5000
10000
15000
20000
25000
30000
35000
40000
GDP PPP per worker

Figure

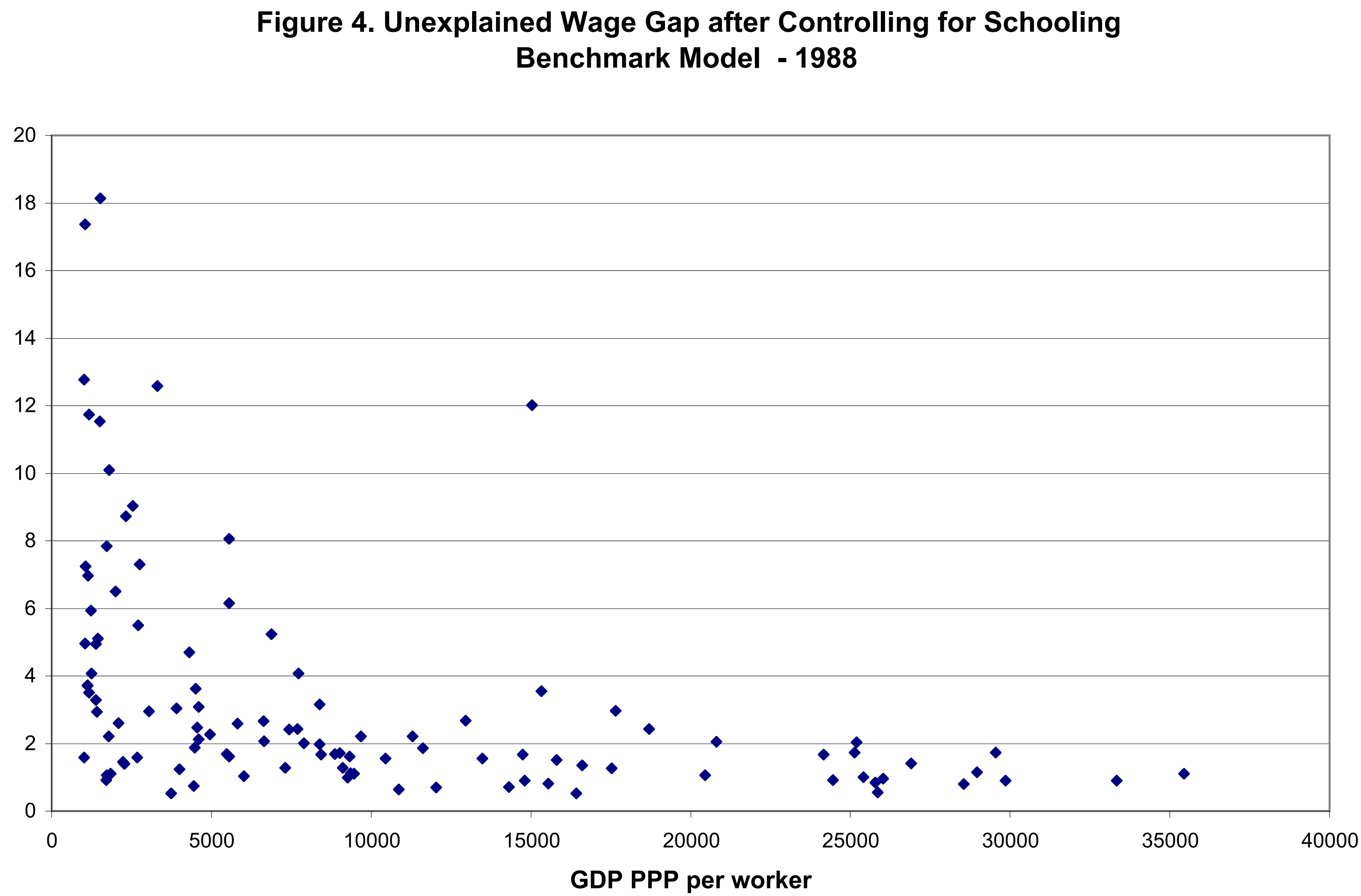
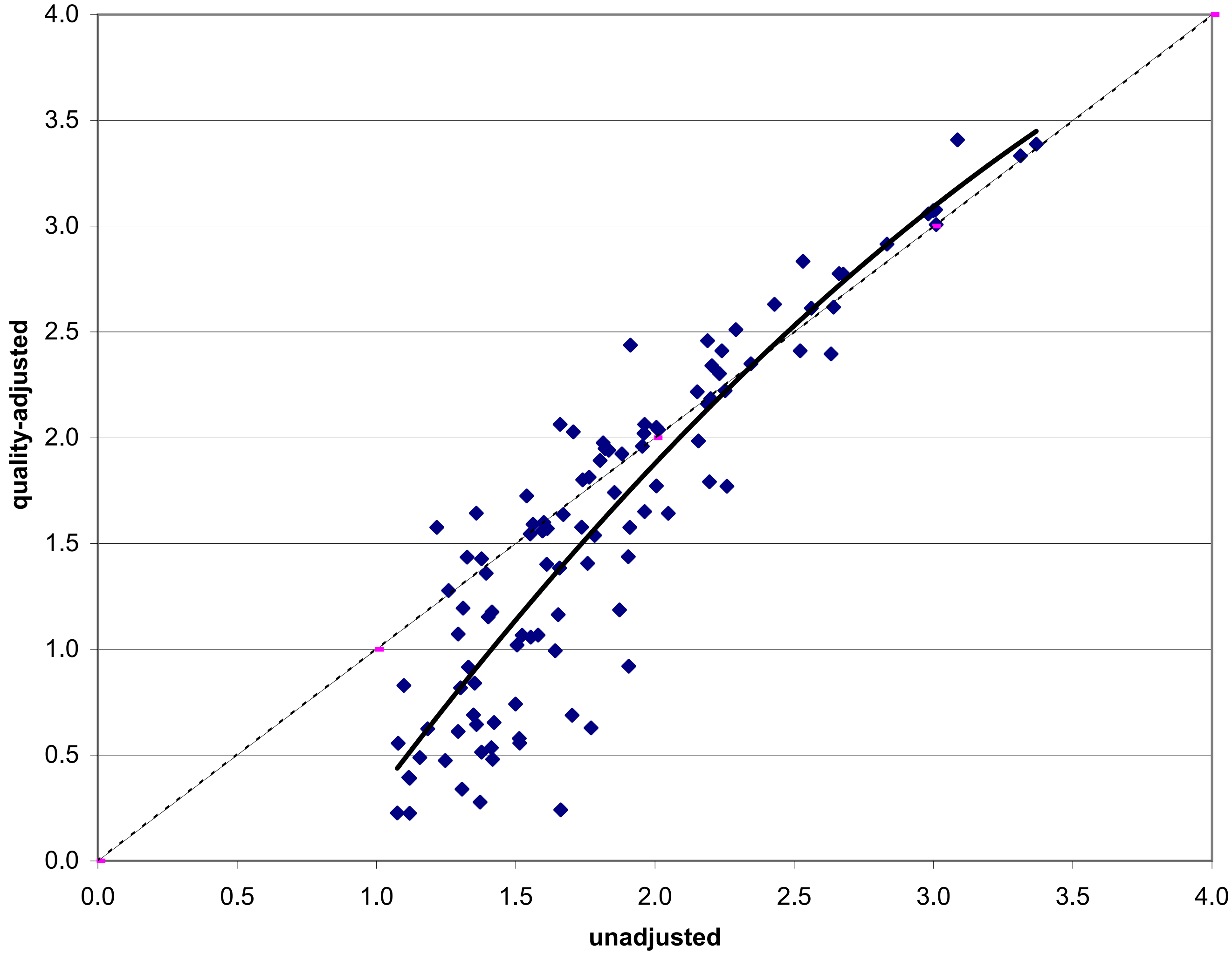


Figure 4. Unexplained Wage Gap after Controlling for Schooling
Benchmark Model - 1988
0
2
4
6
8
10
12
14
16
18
20
0
5000
10000
15000
20000
25000
30000
35000
40000
GDP PPP per worker

Figure 5. Quality-adjusted versus Unadjusted Human Capital - 1988



Figure

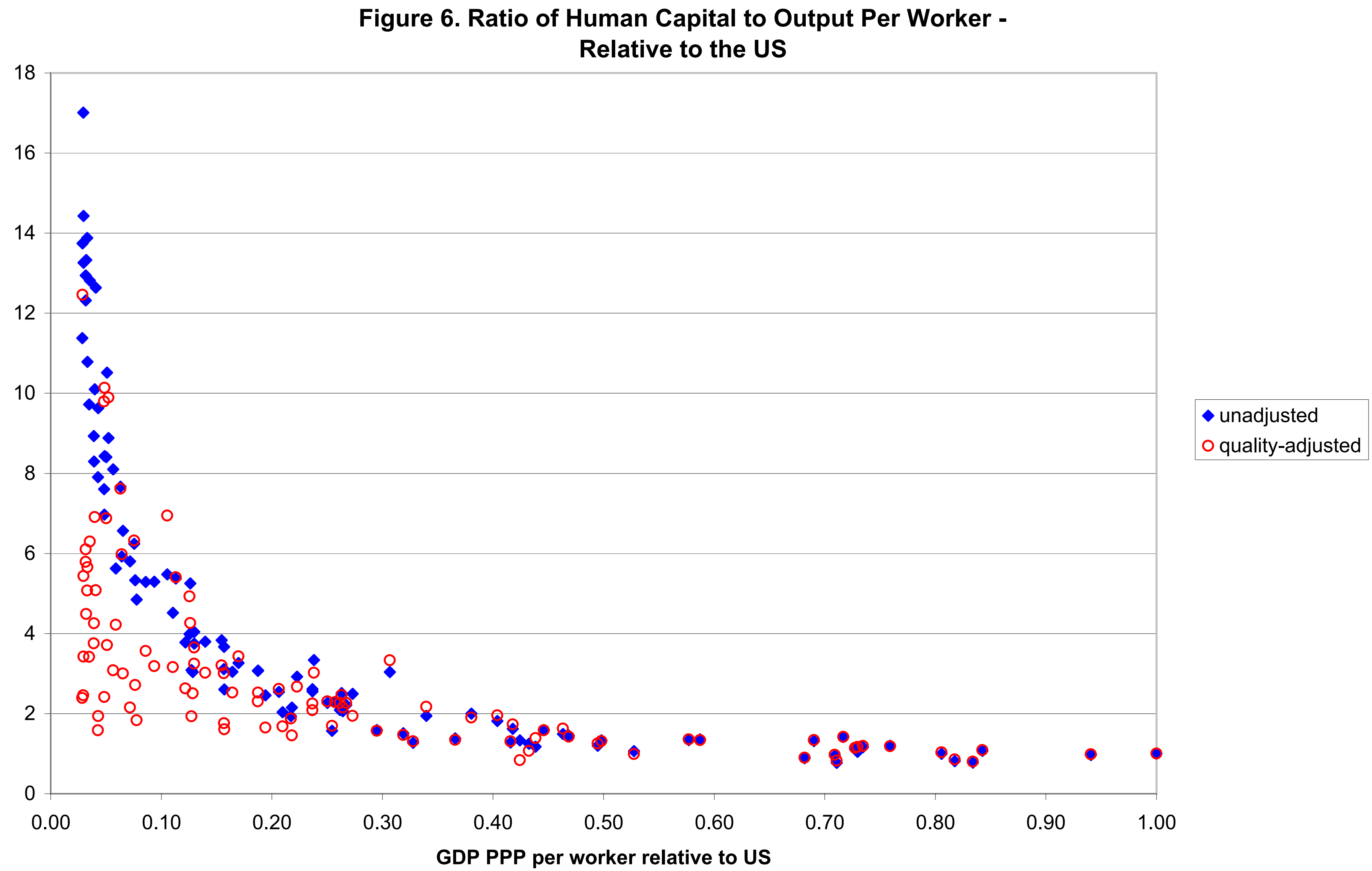
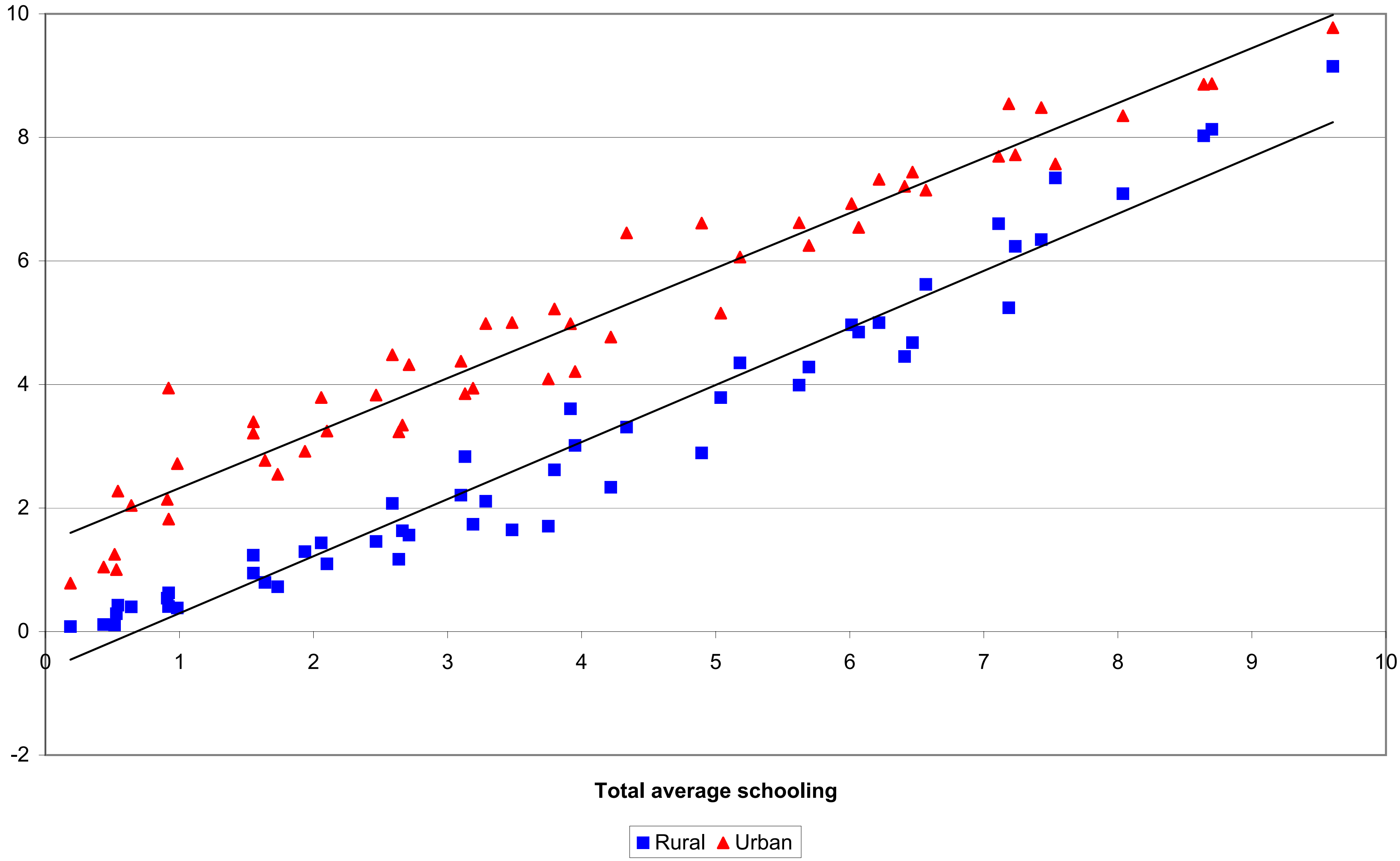


Figure 6. Ratio of Human Capital to Output Per Worker -
Relative to the US
18
16
14
12
10
8
6
4
2
0
0.00
0.10
0.20
0.30
0.40
0.50
0.60
0.70
0.80
0.90
1.00
GDP PPP per worker relative to US
unadjusted
quality-adjusted

Figure

Figure A1. Estimating Urban and Rural Schooling



Table

Table 1. Cross-Country Variance of Sectoral TFPs

$\alpha_n^K = 0.33$, $\alpha_n^H = 0.66$, and $\alpha_n^T = 0.01$

α_a^K	α_a^T	α_a^H	var(lnA_a)	var(lnA_n)	var(lnA)
0.33	0.01	0.66	0.238	0.238	0.238
0.17	0.17	0.66	0.421	0.256	0.238
0.01	0.33	0.66	0.625	0.284	0.238
0.01	0.49	0.50	0.671	0.307	0.238
0.01	0.69	0.30	0.794	0.342	0.238

Table 2. Levels Accounting

Percentage Contribution to Variance - 1988

$\alpha_n^K = 0.33$, $\alpha_n^H = 0.66$, and $\alpha_n^T = 0.01$

α_a^K	α_a^T	α_a^H	Factors	TFP
0.33	0.01	0.66	38	62
0.17	0.17	0.66	36	64
0.01	0.33	0.66	34	66
0.01	0.49	0.50	32	68
0.01	0.69	0.30	30	70

Table 3. Levels Accounting with Quality-adjusted Human Capital

Percentage Contribution to Variance - 1988

$\alpha_n^K = 0.33$, $\alpha_n^H = 0.66$, and $\alpha_n^T = 0.01$

α_a^K	α_a^T	α_a^H	Factors	TFP
0.33	0.01	0.66	66	34
0.17	0.17	0.66	64	36
0.01	0.33	0.66	60	40
0.01	0.49	0.50	57	43
0.01	0.69	0.30	55	45

Table A.1. Adjustment Term Z in Benchmark Model - 1988

Country	Z1*	Z2**
Algeria	1.03	1.08
Angola	1.04	1.10
Argentina	1.02	1.04
Australia	1.01	1.01
Austria	1.00	1.01
Bangladesh	1.10	1.23
Barbados	1.01	1.03
Benin	1.12	1.28
Bolivia	1.06	1.15
Botswana	1.01	1.02
Brazil	1.02	1.05
Burkina Fas	1.11	1.26
Burundi	1.25	1.57
Cameroon	1.07	1.18
Canada	1.00	1.01
Cape Verde	1.05	1.11
Central Afr.	1.20	1.47
Chad	1.13	1.31
Chile	1.02	1.04
Colombia	1.05	1.13
Comoros	1.15	1.34
Congo	1.03	1.08
Costa Rica	1.04	1.10
Cyprus	1.01	1.03
Denmark	1.01	1.01
Dominican I	1.04	1.10
Ecuador	1.04	1.09
Egypt	1.05	1.12
El Salvador	1.06	1.14
Fiji	1.05	1.13
Finland	1.01	1.03
France	1.00	1.01
Gabon	1.02	1.05
Gambia	1.10	1.24
Ghana	1.21	1.49
Greece	1.03	1.08

Country	Z1	Z2
Guatemala	1.08	1.19
Guinea	1.07	1.16
Guinea-Biss	1.28	1.65
Guyana	1.08	1.19
Honduras	1.06	1.14
Hungary	1.04	1.10
Iceland	1.03	1.07
India	1.11	1.25
Indonesia	1.07	1.16
Iran	1.07	1.17
Ireland	1.02	1.05
Italy	1.00	1.01
Jamaica	1.01	1.03
Japan	1.00	1.00
Jordan	1.01	1.03
Kenya	1.11	1.25
Korea, Rep.	1.02	1.05
Lesotho	1.08	1.18
Madagascar	1.12	1.27
Malawi	1.22	1.50
Malaysia	1.05	1.13
Mali	1.18	1.42
Malta	1.00	1.01
Mauritania	1.11	1.26
Mauritius	1.03	1.08
Mexico	1.01	1.03
Morocco	1.05	1.11
Mozambiqu	1.17	1.39
Myanmar	1.28	1.63
Namibia	1.03	1.07
Netherlands	1.00	1.01
New Zealan	1.01	1.03
Nicaragua	1.09	1.22
Niger	1.13	1.29
Nigeria	1.15	1.36
Norway	1.00	1.01

Country	Z1	Z2
Oman	1.00	1.01
Pakistan	1.08	1.19
Panama	1.02	1.05
Papua New	1.09	1.22
Paraguay	1.10	1.23
Peru	1.02	1.05
Philippines	1.07	1.16
Poland	1.03	1.08
Portugal	1.01	1.02
Puerto Rico	1.00	1.00
Romania	1.04	1.09
Rwanda	1.17	1.39
Saudi Arabi	1.01	1.03
Senegal	1.07	1.15
Sierra Leone	1.24	1.56
Somalia	1.41	1.93
South Africa	1.01	1.02
Spain	1.01	1.02
Sri Lanka	1.08	1.19
Suriname	1.02	1.06
Swaziland	1.04	1.10
Syria	1.10	1.23
Tanzania	1.24	1.55
Thailand	1.04	1.10
Togo	1.12	1.27
Trinidad To	1.00	1.00
Tunisia	1.03	1.07
Turkey	1.05	1.11
U.K.	1.00	1.00
Uganda	1.24	1.56
U.S.A.	1.00	1.00
Uruguay	1.03	1.08
Venezuela	1.01	1.03
Zambia	1.04	1.10
Zimbabwe	1.04	1.10

* Corresponds to the case in which land share is agriculture is 0.33 and labor share 0.66.

** Land share in agriculture is 0.69 and labor share is 0.3.

Table A.2. UNESCO Sample for Urban/Rural Schooling

Country	Year
Afghanistan	1979
Algeria	1971
Bangladesh	1981
Brazil	1980
Bulgaria	1992
Cameroon	1976
Canada	1991
Chile	1970
Colombia	1973
Costa Rica	1973
Cuba	1981
Dominican Rep.	1970
Ecuador	1974
Egypt	1986
El Salvador	1971
Estonia	1989
Ethiopia	1994
Greece	1991
Guatemala	1973
Haiti	1986
Hungary	1970
India	1991
Indonesia	1980
Japan	1980
Korea, Rep.	1970
Lebanon	1970
Liberia	1974
Malaysia	1996
Mali	1976
Mongolia	1989
Morocco	1971
Namibia	1991
Nepal	1981
New Zealand	1981
Norway	1990
Panama	1980
Paraguay	1972
Philippines	1995
Poland	1988
Puerto Rico	1970
Romania	1992
South Africa	1970
Spain	1981
Sri Lanka	1981
Sudan	1983
Tunisia	1984
U.S.S.R. (Former)	1989
Tanzania	1988
United States	1970
Uruguay	1996
Venezuela	1990
Zambia	1980

Table

Table A.3. Estimated Rural and Urban Human Capital - 1988

Country	Rural	Urban	Total
Algeria	1.24	1.61	1.38
Angola	1.35	1.74	1.51
Argentina	2.00	2.40	2.24
Australia	2.71	3.04	2.98
Austria	1.99	2.40	2.23
Bangladesh	1.17	1.53	1.30
Barbados	2.15	2.58	2.43
Benin	1.00	1.32	1.10
Bolivia	1.56	1.94	1.76
Botswana	1.45	1.84	1.64
Brazil	1.42	1.80	1.60
Burkina Faso	1.47	1.85	1.66
Burundi	1.18	1.54	1.31
Cameroon	1.21	1.58	1.35
Canada	2.73	3.07	3.01
Cape Verde	1.39	1.78	1.56
Central Afr.R.	1.07	1.41	1.18
Chad	1.27	1.65	1.42
Chile	1.96	2.35	2.19
Colombia	1.61	1.98	1.80
Comoros	1.34	1.73	1.50
Congo	1.36	1.75	1.52
Costa Rica	1.76	2.13	1.95
Cyprus	2.08	2.50	2.34
Denmark	2.72	3.06	3.00
Dominican Re	1.54	1.92	1.74
Ecuador	1.80	2.18	2.00
Egypt	1.72	2.09	1.91
El Salvador	1.43	1.82	1.61
Fiji	2.01	2.42	2.26
Finland	2.58	2.91	2.83
France	1.97	2.37	2.20
Gabon	1.22	1.59	1.35
Gambia	1.02	1.34	1.12
Ghana	1.37	1.76	1.54
Greece	2.01	2.41	2.25

Country	Rural	Urban	Total
Guatemala	1.27	1.65	1.41
Guinea	1.23	1.61	1.37
Guinea-Biss	0.99	1.30	1.08
Guyana	1.73	2.09	1.91
Honduras	1.43	1.82	1.61
Hungary	2.80	3.14	3.09
Iceland	2.24	2.64	2.53
India	1.34	1.73	1.50
Indonesia	1.46	1.85	1.65
Iran	1.38	1.77	1.55
Ireland	2.26	2.66	2.56
Italy	1.92	2.32	2.15
Jamaica	1.54	1.92	1.74
Japan	2.36	2.73	2.64
Jordan	1.57	1.94	1.76
Kenya	1.35	1.74	1.51
Korea, Rep.	2.23	2.63	2.52
Lesotho	1.42	1.81	1.60
Madagascar	1.50	1.88	1.70
Malawi	1.27	1.65	1.41
Malaysia	1.77	2.13	1.96
Mali	1.02	1.34	1.12
Malta	2.04	2.45	2.29
Mauritania	1.26	1.64	1.40
Mauritius	1.62	1.99	1.81
Mexico	1.59	1.96	1.78
Morocco	1.72	2.08	1.90
Mozambiqu	1.05	1.38	1.16
Myanmar	1.18	1.54	1.31
Namibia	1.40	1.79	1.58
Netherlands	2.38	2.75	2.66
New Zealan	3.03	3.39	3.37
Nicaragua	1.47	1.85	1.66
Niger	0.98	1.29	1.08
Nigeria	1.10	1.44	1.22
Norway	2.73	3.07	3.01

Country	Rural	Urban	Total
Oman	1.69	2.05	1.87
Pakistan	1.17	1.52	1.29
Panama	1.93	2.32	2.16
Papua New	1.13	1.48	1.25
Paraguay	1.65	2.01	1.83
Peru	1.84	2.22	2.05
Philippines	1.96	2.36	2.20
Poland	2.35	2.72	2.63
Portugal	1.48	1.86	1.67
Puerto Rico	1.63	2.00	1.82
Romania	1.81	2.19	2.01
Rwanda	1.02	1.34	1.12
Saudi Arabi	1.67	2.03	1.85
Senegal	1.24	1.61	1.38
Sierra Leone	1.14	1.49	1.26
Somalia	1.22	1.59	1.36
South Africa	1.70	2.06	1.88
Spain	1.80	2.18	2.00
Sri Lanka	1.77	2.14	1.96
Suriname	1.19	1.56	1.33
Swaziland	1.47	1.85	1.66
Syria	1.51	1.89	1.71
Tanzania	1.22	1.59	1.36
Thailand	1.72	2.08	1.91
Togo	1.20	1.56	1.33
Trinidad To	1.96	2.37	2.20
Tunisia	1.25	1.63	1.39
Turkey	1.38	1.77	1.55
U.K.	2.40	2.76	2.68
Uganda	1.17	1.52	1.29
U.S.A.	2.99	3.34	3.31
Uruguay	1.96	2.35	2.19
Venezuela	1.77	2.14	1.96
Zambia	1.58	1.95	1.77
Zimbabwe	1.27	1.66	1.42

Table

Table A.4. Quality-adjusted Human Capital: Rural, Urban and Total -1988

Country	Rural	Urban	Total
Algeria	0.95	1.61	1.43
Angola	0.16	1.74	0.56
Argentina	2.46	2.40	2.41
Australia	3.30	3.04	3.06
Austria	1.27	2.40	2.30
Bangladesh	0.47	1.53	0.82
Barbados	3.34	2.58	2.63
Benin	0.56	1.32	0.83
Bolivia	0.83	1.94	1.41
Botswana	0.15	1.84	0.99
Brazil	0.85	1.80	1.56
Burkina Fas	0.11	1.85	0.24
Burundi	0.23	1.54	0.34
Cameroon	0.32	1.58	0.69
Canada	3.32	3.07	3.08
Cape Verde	1.19	1.78	1.59
Central Afr.	0.44	1.41	0.62
Chad	0.26	1.65	0.48
Chile	1.34	2.35	2.16
Colombia	1.68	1.98	1.89
Comoros	0.46	1.73	0.74
Congo	0.40	1.75	1.07
Costa Rica	1.52	2.13	1.96
Cyprus	1.52	2.50	2.35
Denmark	3.28	3.06	3.07
Dominican I	1.47	1.92	1.80
Ecuador	1.00	2.18	1.77
Egypt	0.92	2.09	1.58
El Salvador	1.16	1.82	1.57
Fiji	1.01	2.42	1.77
Finland	2.98	2.91	2.91
France	1.88	2.37	2.34
Gabon	0.22	1.59	0.84
Gambia	0.19	1.34	0.39
Ghana	1.70	1.76	1.72
Greece	1.63	2.41	2.22

Country	Rural	Urban	Total
Guatemala	0.75	1.65	1.18
Guinea	0.10	1.61	0.28
Guinea-Biss	0.43	1.30	0.56
Guyana	3.63	2.09	2.44
Honduras	0.89	1.82	1.40
Hungary	4.83	3.14	3.41
Iceland	4.42	2.64	2.83
India	0.64	1.73	1.02
Indonesia	0.62	1.85	1.16
Iran	1.21	1.77	1.55
Ireland	2.35	2.66	2.61
Italy	1.23	2.32	2.22
Jamaica	0.61	1.92	1.58
Japan	1.27	2.73	2.62
Jordan	1.12	1.94	1.81
Kenya	0.29	1.74	0.58
Korea, Rep.	1.58	2.63	2.41
Lesotho	1.29	1.81	1.60
Madagascar	0.37	1.88	0.69
Malawi	0.37	1.65	0.54
Malaysia	1.75	2.13	2.02
Mali	0.25	1.34	0.40
Malta	4.25	2.45	2.51
Mauritania	0.81	1.64	1.15
Mauritius	1.90	1.99	1.98
Mexico	0.53	1.96	1.54
Morocco	0.71	2.08	1.44
Mozambiqu	0.31	1.38	0.49
Myanmar	1.07	1.54	1.20
Namibia	0.36	1.79	1.07
Netherlands	3.27	2.75	2.78
New Zealan	3.33	3.39	3.39
Nicaragua	2.56	1.85	2.06
Niger	0.11	1.29	0.23
Nigeria	1.74	1.44	1.58
Norway	2.13	3.07	3.01

Country	Rural	Urban	Total
Oman	0.16	2.05	1.19
Pakistan	0.68	1.52	1.07
Panama	1.06	2.32	1.98
Papua New	0.22	1.48	0.47
Paraguay	1.84	2.01	1.94
Peru	0.64	2.22	1.64
Philippines	1.15	2.36	1.79
Poland	1.55	2.72	2.40
Portugal	0.70	1.86	1.64
Puerto Rico	0.93	2.00	1.95
Romania	1.62	2.19	2.04
Rwanda	0.13	1.34	0.23
Saudi Arabi	0.78	2.03	1.74
Senegal	0.20	1.61	0.51
Sierra Leone	1.18	1.49	1.28
Somalia	1.66	1.59	1.64
South Africa	1.12	2.06	1.92
Spain	1.19	2.18	2.05
Sri Lanka	1.15	2.14	1.65
Suriname	1.00	1.56	1.44
Swaziland	0.73	1.85	1.38
Syria	2.29	1.89	2.03
Tanzania	0.47	1.59	0.64
Thailand	0.31	2.08	0.92
Togo	0.59	1.56	0.92
Trinidad To	0.73	2.37	2.18
Tunisia	0.74	1.63	1.36
Turkey	0.46	1.77	1.06
U.K.	3.15	2.76	2.77
Uganda	0.45	1.52	0.61
U.S.A.	2.99	3.34	3.33
Uruguay	3.06	2.35	2.46
Venezuela	1.55	2.14	2.06
Zambia	0.19	1.95	0.63
Zimbabwe	0.21	1.66	0.65